

Tracking fishermen: using GIS to characterise spatial distribution of fishing effort in the Tasmanian abalone fishery

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Submitted in fulfilment of the requirements for
the Degree of Master of Science
University of Tasmania

November 2011

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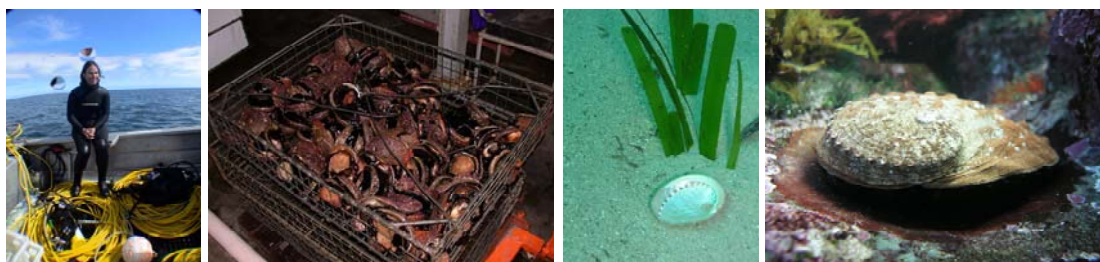
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Abstract

Major collapses of abalone fisheries around the world have been preceded by a spatial serial depletion of abalone populations. As in other fisheries, this serial depletion has been difficult to anticipate and to understand without fine scale monitoring and analysis of spatial effort distribution. In recent years a field of fisheries science has started to evolve which looks at the spatial distribution of fishing effort in commercial fisheries and spatial fleet dynamics, and novel applications of some GIS tools are being developed. Despite the relative health of the Tasmanian abalone fishery (a \$A100 million fishery) compared to other abalone fisheries around the world, many aspects of the reporting and assessment process require improvement to ensure sustainability of the fishery. History has shown that reliance on catch and temporal effort data reported at large spatial scales (current Tasmanian practice) is inadequate for assessment of abalone stocks, or for detecting spatial depletion. Traditional fishery independent methods used to estimate population abundance (both relative and absolute) are also inadequate, and prohibitively expensive for monitoring fishery stability.

In this study, GPS data loggers were deployed on abalone fishing boats and set to record latitude and longitude of boat position every ten seconds. Divers wore depth loggers to record information about when divers were actively fishing. A novel aspect of this study is the combination of GPS fishing data and GIS tools, generally applied in animal behaviour analyses, to quantify the spatial distribution of fishing effort as captured by the loggers. The ability of these methods to describe complexity of diver behaviour, concentration of diver effort and contraction of the fishery were assessed.

The use of GPS loggers provided high spatial resolution data on fishing activity, and improved the quality of fishing effort data available. Describing spatial distribution of fishing effort at fine scales captures information about changes in that spatial distribution. Performance measures of Catch Per Unit of Area fished were developed and demonstrated in the context of fishery assessment. Kernel density estimates of fishing activity during single fishing events are proposed as measures of fishing behaviour. Adoption of simple behavioural indices (dive duration as an indicator of fishing success) was proposed to enhance traditional Catch Per Unit Effort based stock-assessment methods. Subject to field validation, the performance measures developed in this study can be used to forewarn fishers and advise managers of depleting fish stocks.



Acknowledgements

This thesis has been a voyage taken in excellent company. I would like to thank my supervisors, Craig Mundy, Arko Lucieer and Malcolm Haddon. You each played different and important roles in the development and completion of this thesis. This project was conceived by Craig while working as the head of the TAFI Abalone Research Group. Thank you for your inspiration, your ongoing input, advice and guidance and for giving me the opportunity to work on such an exciting project. Thank you, Malcolm, for sharing your expertise, insight and your wide understanding of fisheries management. Arko, you have helped to guide me from the start and have steered me out of eddies all along the way. Martin Marzloff provided invaluable advice about the statistics I used in Chapter 3. I often discussed the ideas behind my work with Martin and he helped me to articulate my thoughts more clearly.

Thank you to everyone in the Abalone Research Group at TAFI, and in particular to David Tarbath who helped me to unearth old stock status and assessment reports from pre-MRL days. To the divers who participated in data collection, a thousand thanks. I hope that you know how much your contribution has meant to me. I extend my recognition to the Tasmanian Abalone Council who with the University of Tasmania provided me with a scholarship to embark on this thesis.

The School of Geography and Environmental Studies at UTAS have provided precious support and have given me a place to sit, space to think and patience to let me finish this journey. Rob Anders has come through with ArcGIS support countless times. I would especially like to thank Jon Osborn for his occasional mentorship and for having faith that I would reach my destination.

Thank you to Julie Coad, Tracy Payne, Trish McKay and Paulene Harrowby who have made the administrative side of candidature simple and painless. Thank you to all of the people at CenSIS for your comradeship and fantastic humour: Phillippa, Michael, Theresa, Richard, Jenny, Chris and Thor.

My family and my friends have fed me good food, bolstered my morale with bushwalking plans and kept up a steady stream of cups of tea. Thank you!

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CHAPTER 1 INTRODUCTION

1.1 A Problem: Abalone fisheries are collapsing

Abalone are marine molluscs that are expensive gastronomic delicacies in many parts of Asia. The growth of international trade in the last century has meant that intense fishing pressure has been placed on wild populations of abalone. Because of excessive fishing pressure USA abalone stocks have regressed from valuable fisheries to being in a state of commercial non-viability (Figure 1). The British Columbia fishery was closed in 1990 and through the 1990's there was no evidence of significant fishery recovery (Jamieson 2001). The Mexican abalone fishery has also suffered from over-fishing and while still viable it is operating at a much smaller scale than previously (Leiva and Castilla 2001). The South African abalone fishery was closed on the 1st of November 2007 (Benton 2007). Due to this string of fishery collapses and closures elsewhere, Australia now supports the most productive wild fishery for abalone in the world. Tasmania is currently the source of almost half of Australia's abalone catch and in 2005 was the source of 28% of global catch (calculated from FAO catch records and Tasmanian catch reporting records from the Tasmanian Aquaculture and Fisheries Institute).

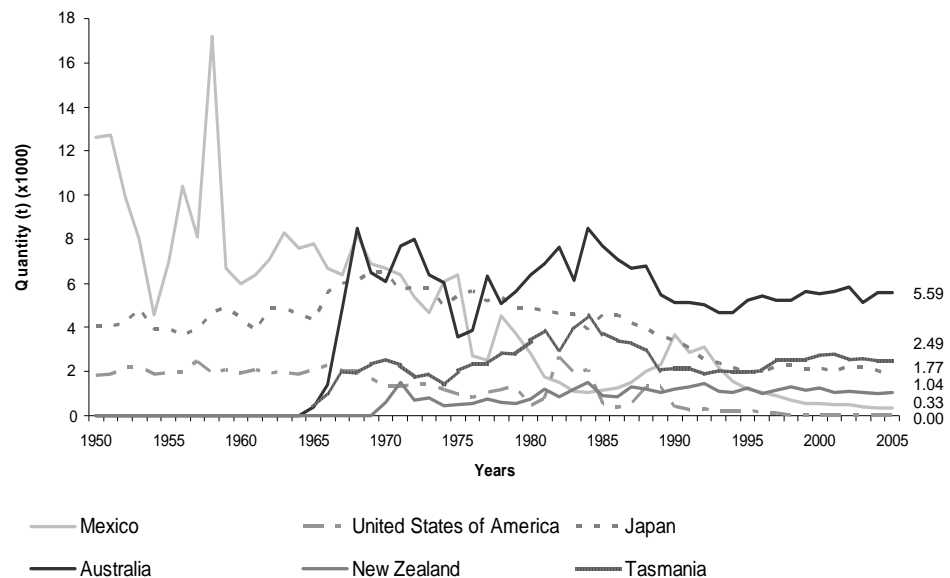
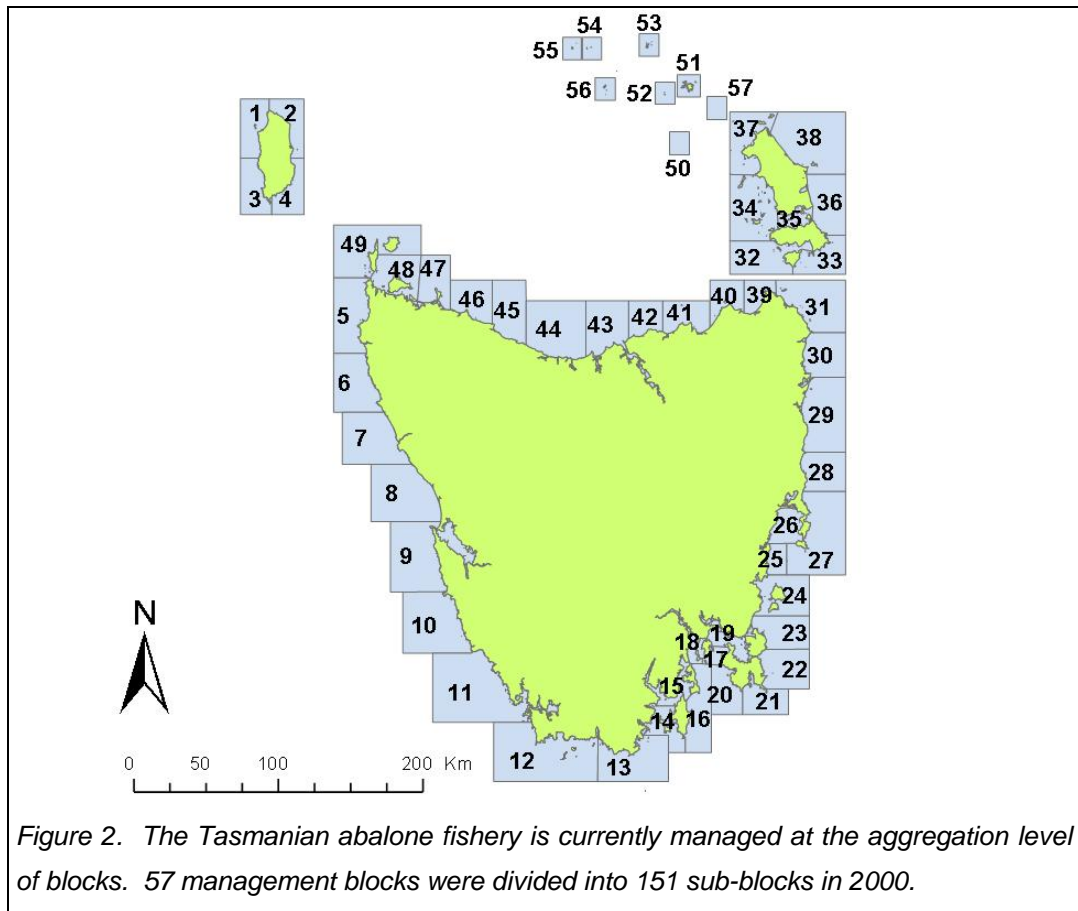


Figure 1. Global abalone catch (*Haliotis* spp.) from 1950 to 2005, from the FAO (FAO 2008). Tasmanian abalone catch 1965-1974 from the South Eastern Fisheries Committee Abalone fishery situation report 10 (Dix et al. 1982) and 1974-2005 from the TAFI abalone catch database (TAFI 2008).

1.2 A Culprit: Catch rates as an index of stock abundance

Abalone fisheries traditionally have been managed using trends in Catch Per Unit Effort (CPUE) as indicators of stock abundance. CPUE is defined as the amount of catch taken by a vessel or by a fleet with application of a defined unit of effort (Breen 1992). Across a range of fisheries, effort can be measured using several different dimensions including duration of trawling, gear units (e.g. number of hooks in a set) (Bordalo-Machado 2006) and for abalone fisheries worldwide the number of hours spent diving (Breen 1992). In Tasmania, CPUE is reported by abalone divers to the State fisheries management organisation (Fisheries Branch, Department of Primary Industries, Parks, Water and Environment) through a paper docket system. Daily catch is reported in kilograms, and the time spent diving for each day is estimated and reported in hours (Tarbath *et al.* 2007). Catch and associated effort is reported within defined spatial units (blocks). The size of reporting blocks range from 20km to 60km. Thus, the scale at which fishing activity is captured spans 10's of kilometres of coastline. In Tasmania, there are 57 abalone blocks, divided into 151 sub-blocks (Figure 2). In addition, the fishery is formally divided into separate zones to ensure effort is distributed sustainably. In 2007, the Tasmanian blacklip (*Haliotis rubra*) fishery was partitioned into Eastern, Western, Northern and Bass Strait zones, with a further greenlip (*Haliotis laevis*) specific zone (Tarbath *et al.* 2007).

It is generally accepted that reliance on CPUE as a key performance measure has contributed to management failure in abalone fisheries worldwide. CPUE was used for stock assessment for fisheries in California and Mexico prior to their collapse (Karpov *et al.* 2000). Despite this, abalone fishery assessments in Tasmania and world-wide still rely heavily on catch rate recorded at relatively coarse spatial scales as the principle performance measure (Prince 2005).



1.2.1 Abalone fisheries contravene CPUE assumptions

CPUE is not an ideal stock assessment tool or performance measure for abalone fisheries because these effort measures contravene key assumptions upon which the method relies, i.e. that across a sampled area:

- the stock is homogenous in distribution and
- fishing is randomly distributed (Salthaug and Aanes 2003)

All abalone species are patchily distributed and are made up of extensive meta-populations (Shepherd and Brown 1993, Morgan and Shepherd 2006) within which the many sub-populations can have different biological properties of growth and productivity (Prince 2003). Under the same fishing conditions, some sub-populations will persist while others can not sustain themselves (Prince 2005). Given the typical distribution patterns of most haliotids, the assumption of homogeneous stocks is rarely valid. The fragmented spatial structure of meta-populations leads to fragmented fishing behaviour and non-random distribution of fishing effort (Karpov *et al.* 2000).

1.2.2 Mismatch of scale masks stock depletion

In many fisheries, stock collapse has been preceded by a dramatic contraction of the spatial extent of the stock (e.g. Atkinson *et al.* 1997), and by spatial re-organisation of fishing activity as fishers respond to changing stock availability (e.g. Salthaug and Aanes 2003, Verdoit *et al.* 2003, Bertrand *et al.* 2004). Unsustainable levels of localised fishing can cause local population contractions and depletions. These local depletions are not detectable when catch data are aggregated at an inappropriate gross scale (Prince 2005). Spatial serial depletion¹ of fish populations can be masked by common fishery statistics if they are applied to data aggregated from large geographical areas relative to the fine scale of real effort (Breen 1992). Consequently, CPUE can indicate apparently stable catches in an area even while serial depletion and removal of sub-populations is occurring within a management block of aggregated data (Davis *et al.* 1992, Karpov *et al.* 2000). In the Tasmanian abalone fishery the current scale of reporting of data on catches, location of catches, and effort is very coarse (10^4 m) (Tarbath *et al.* 2007) relative to the scale of both the biological processes of recruitment and population structure (Morgan and Shepherd 2006, Miller *et al.* 2009) and to the scale of fishing activity (10^2 m) (Prince 2005).

Serial depletion of a fishery can also occur when the catchability of a stock is not homogenous. For example, as easily accessible abalone are removed from a fished population, fishing effort will shift to other sections of the population, e.g. to deeper water, more exposed coastline, or more distant reefs, as in the Californian abalone fishery in Karpov *et al.* (2000). If serial local depletions or local extinctions are not detected they may ultimately result in fishery collapse (Hobday *et al.* 2001). Prince & Shepherd (1992) argue that abalone stocks are prone to spatial serial depletion in a manner that is difficult or impossible to detect using traditional stock status performance measures. Prince (2003) coined the phrase a “tyranny of scale”

¹ *serial depletion*: As effort increases and fisheries yield declines due to diminishing population sizes, fishers either move elsewhere to fish (geographic expansion, intra-specific serial depletion) or change target fishery species to continue fishing (exploitation of previously spurned species lower in the food web, inter-specific serial depletion) (Pauly *et al.* 2002). Serial depletion has been observed in many fisheries worldwide including crab, shrimp and urchin fisheries (Orensanz *et al.* 1998). The progressive depletion of separate sub-populations of abalone is an example of intra-specific serial depletion (Hobday *et al.* 2001)

to articulate the mismatch in scales of reporting and fishing. Prince also asserts that research and monitoring of highly structured stocks like abalone is prohibitively expensive and generally not done well, if at all. Given the poor performance of CPUE based performance measures, there remains a management need for alternative fishery performance measures that can capture the fine scale spatial nature of abalone fisheries and that can act as proxies for stock abundance.

Intra-specific serial depletion of fisheries can occur in two different ways: 1) In the absence of size limits, it is the sequential removal or extinction of populations (e.g. fishery declines in California, Mexico and Japan); 2) With size limits (intended to maintain a sufficient number of mature individuals) but with an unsustainable Total Allowable Catch, it is the sequential depletion of fishable populations beyond the productivity of those populations (e.g. West coast of Tasmania) (Mundy 2005). In the latter case, if allowed sufficient time, there is good biological reason to expect that these populations will recover. Recovery time will depend on the productivity of individual populations (Morgan and Shepherd 2006).

1.2.3 Measures of fishing activity do not capture spatial information

In addition to the mismatch of scales of fishing activity and catch reporting, each fishing event² encompasses diver behaviour that has a spatial component not taken into account by current catch rate estimates. Unlike the units used to measure effort in trawl fisheries (duration of trawling in h hours with n gear units travelling at x speed) (Bordalo-Machado 2006), abalone fishing effort measured in hours does not integrate any spatial information (distance, area, volume). It is not possible to know whether a diver has searched a large or small area to take their catch when data on the very fine scale distribution of fishing effort during a day is not available. If the density of abalone varies at different places or times, a diver may search a greater area to take the same amount of catch, possibly within the same amount of time. The speed at which a diver swims can also be highly variable and dependent on the abundance and distribution of abalone (Beinssen 1979).

² *fishing event*: a single dive event, commencing when a diver enters the water and ending when the diver leaves the water.

1.3 A Solution: Record the location and spatial extent of fishing activity

Detailed information on fishing location would enable calculation of site-specific CPUEs. Data on diver swim speed and search patterns could provide the spatial variables (speed, volume/area) that are available when calculating CPUE for a trawl vessel, but these parameters are not available when calculating catch rate in an abalone fishery. Babcock *et al.* (2005) describe a need for the knowledge and skills of landscape ecologists, who work with spatial data in a GIS environment, to be integrated with the knowledge and skills of fisheries scientists, who use population dynamics models and statistical tools for fisheries management. They propose that cooperation between these fields of research would progress the design of spatial management measures and help prevent bias in trends caused by spatial heterogeneity.

Global Positioning System (GPS) loggers have offered a significant advance in techniques for studies of fine-scale animal movement patterns (Ryan *et al.* 2004). In the field of animal behaviour studies, Geographical Information System (GIS) analysis tools have been developed to investigate the relationship between foraging patterns of predators and spatial distribution of prey, e.g. Ramos-Fernandez *et al.* (2004), Garthe *et al.* (2007). If measures of fisher behaviour can provide reliable alternative estimates of CPUE/stock abundance, as demonstrated in a novel application for the Peruvian trawl fishery (Bertrand *et al.* 2004, Bertrand *et al.* 2005) then these measures may become valuable as abalone fishery performance indices that can be used independently of CPUE.

Two spatial issues could be addressed with fine-scale spatial information; the precise location of the site of fishing effort expenditure, and development of a spatial performance index that captures the response of a diver to stock density. In the absence of tested alternative measures, a CPUE estimate that integrates fine scale spatial patterns will be more informative to managers than CPUE calculated at a scale of management blocks. Fine-scale changes in CPUE could indicate a change in local availability of abalone. If effort is measured with a spatial or volumetric component instead of only in hours, fluctuations in abalone density may be captured. Quantitative metrics that describe fishing behaviour could eventually link foraging behaviour to prey abundance. New spatial performance measures that

do not assume random fishing will, ideally, eventually supplement or replace traditional fishery statistics in abalone fishery stock assessment.

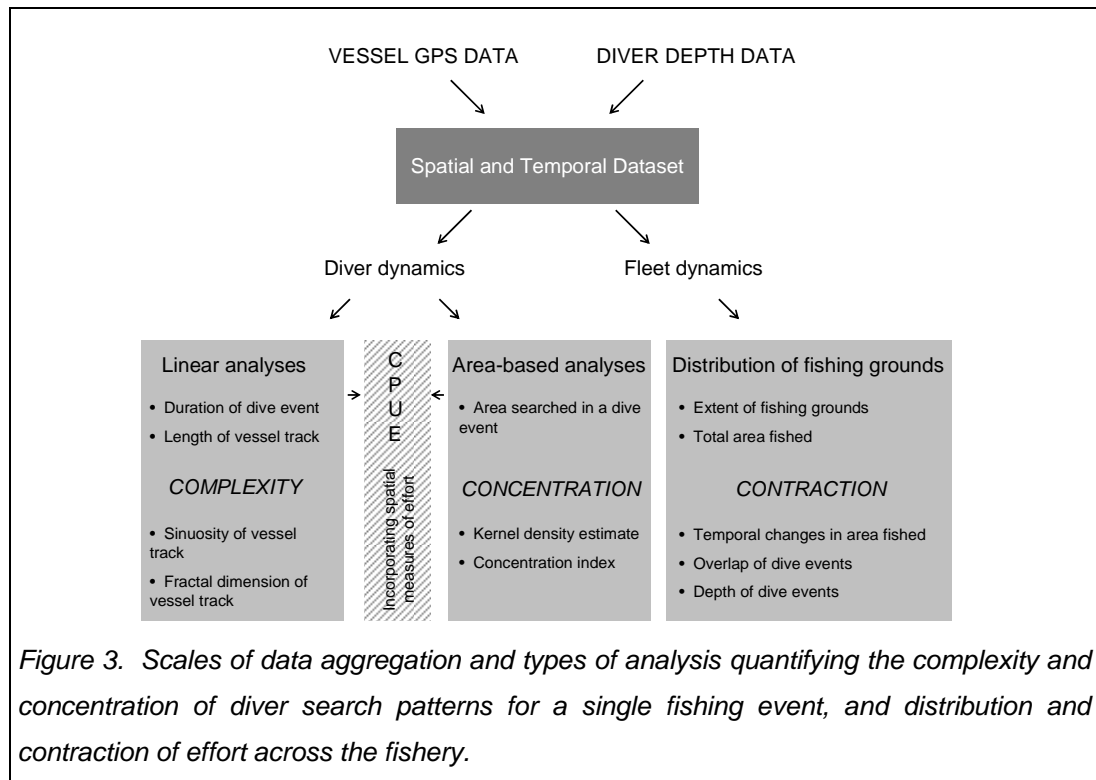
Through this study I tested spatial analysis techniques that may be used in conjunction with each other to improve management decisions in three major ways:

- 1) by focusing on estimates of CPUE at the scale at which fishing occurs, i.e. at the scale of an individual diver harvesting sub-populations of abalone rather than across the whole fleet at the scale of management blocks.
- 2) By using fine-scale spatial information about individual fishers' behaviour to integrate the spatial component of fishing activity into distance- and area-based indices of fishing effort;
- 3) By developing a spatial behaviour-based index of fishing performance independent of CPUE that can be used in parallel with catch rate information to quantify the degree of non-randomness and non-homogeneity of diver fishing behaviour.

In order to develop these techniques, data have been collected with the cooperation of a subset of divers within the Tasmanian abalone industry. These volunteer project participants carried GPS data loggers on their vessels and depth/temperature loggers on their person while diving. The data collected were both spatial and temporal and included precise location, time and depth of fishing activity. The data collection methods are described in detail in Chapter 2.

1.4 Scales of Investigation

For this thesis, diver data have been aggregated and analysed at two different scales: a) diver dynamics during a single fishing event, and b) fleet dynamics across multiple fishing events (Figure 3).



1.5 Aim and Objectives

Using the example of the Tasmanian abalone fishery, the aim of this study is to test and illustrate the value of collecting fine-scale spatial information about the fishing activity of individual fishers to support monitoring, assessment and management of a small-vessel coastal fishery.

In this thesis, four main objectives are addressed:

1. Firstly, in Chapter 2, I present the methods used to collect fine-scale spatial data from a small sample (three volunteer divers) of the Tasmanian abalone fishery. Based on the successes and impediments encountered during this exploratory sampling of fine-scale fishing activity, recommendations are made to guide future studies;
2. In Chapter 3, I describe a range of indices of fishing effort derived from fine-scale monitoring of fishing activity. I identify a number of spatial analysis methods and GIS tools that can be applied to quantify fine scale spatial abalone catch and effort data and demonstrate the application of these methods to fisheries data. Due to unanticipated technical failures that occurred during sampling, data had to be filtered prior to analysis. Only a subset of data from three individual divers was used to test the value of fine-

scale monitoring of fishing effort to complement traditional measures of fishing activity (CPUE) with some alternative distance-based and area-based indices of fishing effort;

3. In Chapter 3, I also assess the ability of these fine-scale indices of fishing activity to distinguish different fishing behaviours and identify different sub-groups of behaviour within data sets;
4. In Chapter 4 I focus on area-based measures of divers' abalone harvesting behaviour as indices to capture concentration of diver effort. Such spatial indices can potentially provide catch-independent information about fine-scale fishing efficiency. I also discuss limitations of the indices.

CHAPTER 2 DATA COLLECTION AND PROCESSING

2.1 Introduction

Since 2005, researchers at the Tasmanian Aquaculture and Fisheries Institute (TAFI) have been developing electronic tools to improve the quality and resolution of fishery dependent data in the Tasmanian abalone fishery, a dive fishery. These tools are a passive Global Positioning System (GPS) data logger to record fine scale spatial information on the location of fishing activity, and an automatic depth/temperature recorder to obtain an accurate record of time and depth of each fishing event. The research has been funded by TAFI and in 2006, additional funding was received from the Australian Fisheries Research and Development Corporation (FRDC) to continue the development process (FRDC 2006/029). Diver participation in the research program is voluntary and participation numbers have increased from two divers in 2005, to approximately 20 divers in 2007. This represents twenty percent of the active divers working in the fishery.

The collection of fine scale fishery dependent data for a dive fishery is a novel undertaking and the data logging approach has been developed to complement the particular way that an abalone diver works while fishing. In the Tasmanian fishery, abalone divers generally work from a 'live' (i.e. not anchored and with motor running) vessel that is driven by a deckhand. The deckhand is also responsible for the compressor that supplies air to the diver through a high-pressure hose, for deploying empty catch bags to, and retrieving full bags from the diver, and packing abalone into bins. Divers travel from boat ramp to dive site either on a small vessel (~16 ft) or, for more remote locations, on a 'mother ship', a larger boat carrying one or more smaller tenders and with facilities to store live abalone for extended periods.

On arrival at a dive site, divers enter the water with an abalone iron (a bar used to lever or flick abalone from reef and rocky substrates) and collect abalone across the extent of the reef or site. Different divers may have different search and fishing patterns, and these patterns are highly likely to be influenced by the weather (wind speed and direction and swell height), visibility conditions, macroalgal density, depth, bathymetry and surface or reef roughness, and potentially other factors. While fishing, deckhands will drive the vessel to follow a diver, being directly above

the diver when retrieving catch bags and in reasonably close proximity to the diver for the full duration of a fishing event. When a diver exits the water, the vessel may travel over distance to a different dive site to continue fishing. A GPS data logger captures data on vessel location throughout each dive and an automatic depth/temperature logger captures the time of diver entry to and exit from the water, and the depth profile of the dive. These data sets were combined to identify the location of the vessel when the diver was in the water.

2.1.1 Objectives

The objectives of this chapter are to:

- Describe the equipment used to collect fine scale spatial data from abalone divers working in the Tasmanian fishery.
- List the parameters that are measured by this equipment.
- Outline the dataset that was compiled for spatial analysis in this thesis.
- Identify problems encountered during data collection for this project.

2.2 GPS Receiver and Data logger

2.2.1 Design and Specifications

GPS Data loggers (MK0) for the project were designed to TAFI specifications by SciElex, a marine electronics company based in Kingston, Tasmania (Cfish 2004). Starting in 2004, two progressively more flexible models of GPS data logger were developed (MKI, MKII). Each of the GPS loggers had integrated non-differential 12 channel GPS receivers. The Haicom Hi-204S was used in all earlier models (MK0 and MKI loggers). The MK0/MKI loggers recorded standard National Marine Electronics Association (NMEA) output data from the receiver with date and time in UTC0, and had a capacity of 1,048,576 records (approximately 120 days of continuous recording at 10 sec intervals, 24 hours/day). The datum for Latitude and Longitude was WGS84. The manufacturer's specifications for the Hi-204S listed accuracy as 25m (Haicom_Electronics_Corporation 2005). Both MK0 and MKI GPS loggers required an external 12V power supply. On diver's boats, power was supplied to these GPS loggers either from on-board power or from a sealed lead-acid 12V battery (see Figure 4). MKII GPS loggers were powered internally by 4 x 1.2v batteries in series providing 4.8V for approximately 40 hours of run time, and

used a Fastrax uPatch100-S GPS receiver (Fastrax Limited 2006)³. Standard NMEA strings were captured from the module. Memory in the MKII loggers was a 128MByte Flash Card providing capacity for more than 2 million samples. Each GPS receiver and logger was encased in a robust, waterproof housing (Figure 4).

Data were downloaded from the MK0 and MKI GPS data loggers via a serial port using the Windows HyperTerminal interface. Data were saved in standard NMEA format to a CSV file. The MKII GPS loggers were supplied with download software which performed some basic data management functions such as conversion of raw time and date fields into a combined date/time field in a user selected UTC time zone.

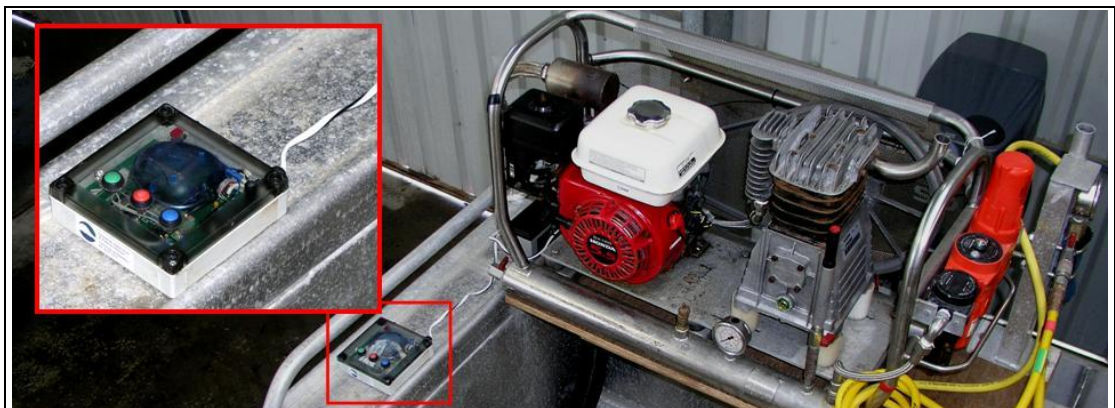


Figure 4. A MKI GPS data logger with Haicom Hi-204S GPS receiver and external 12v power supply, here installed on a diver's vessel next to the air compressor. Credit: TAFI Abalone Group Image Collection, 2007.

2.2.2 Sampling Frequency

Provided that there was adequate satellite reception, the GPS data loggers were capable of recording a constant stream of position data at any sampling frequency up from one second intervals. Turchin (1998) stated that when sampling movement paths the sampling frequency should match the scale of change or the scale of movement⁴. As this research project was focussed on capturing and quantifying

³ Two MKII loggers (MKIIA) were produced with Haicom Hi-204S GPS receivers. Data from these loggers were not used in analyses, for reasons outlined in Ch 2 Section 2.3.

⁴ Inappropriate sampling frequency is referred to as undersampling, or oversampling.

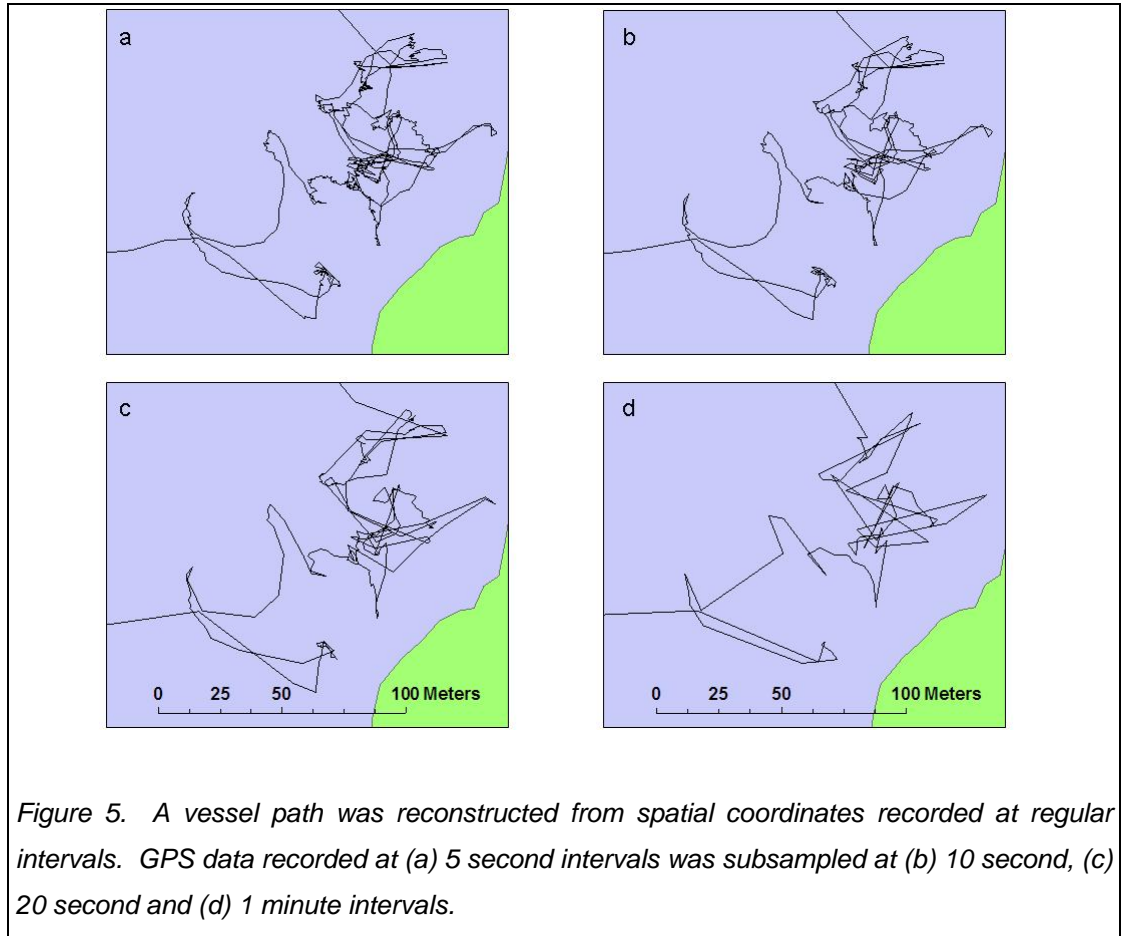
Undersampling can occur when position data are recorded at a temporal scale that is too coarse, leading to loss of important movement information. Undersampling has been

diver behaviour (e.g. the amount of area searched and the complexity and concentration of fishing activity) during single fishing events the GPS data logger sampling frequency was chosen to be at the same scale as that of vessel movement around a dive site.

In a pilot study, testing against undersampling was performed on data collected at a very high temporal resolution, i.e. at 5 second intervals. As suggested by Kareiva and Shigesada (1983), the data were sub-sampled at several different time intervals and the sampling interval chosen that provided movement parameters which most accurately reflected the complexity of the vessel path while minimising the number of data points to be analysed (Figure 5). This was a subjective, visual assessment. Subsequently, the recording frequency of GPS loggers was set to an interval of 10 seconds.

For most of the project, divers were asked to leave the GPS data loggers running for the full duration of a fishing day. This would provide a continuous 10 second datastream for full days of fishing and commuting activity. However, early issues with unreliable power supply, unstable battery connections and/or insufficient battery charge for MK0 and MK1 data loggers resulted in many of the divers switching the GPS loggers off after each dive.

recognised in a fisheries context during analysis of Vessel Monitoring System (VMS) position information collected from vessel operating in a trawl fishery (Deng *et al.* 2005) and can underestimate track lengths by, for example, up to 50% in the case of African penguin tracking (Ryan *et al.* 2004). Oversampling can occur when position data are recorded at a finer temporal scale than the scale of movement and leads to repetitive sampling of the same position (Turchin 1998). There can be a trade-off between sampling rate and battery lifespan. Oversampling in the field is recognised as less of a problem than undersampling because oversampled datasets can be subsampled later and no information is lost (Turchin 1998).



2.2.3 Testing for error in GPS data

The MKI and MKIIA loggers used Haicom GPS receivers which were less accurate than the Fastrax GPS receivers used in MKIIB loggers and also less accurate than many other non-differential 12 channel GPS receivers (generally considered to have accuracy in the order of $\pm 5 - 10$ m). Limited accuracy of non-differential receivers is due to errors in the satellite signal reception caused by ionospheric delays, geometric dilution of precision, time ambiguities, and multipath reflections (Jeffrey and Edds 1997). During data collection trials it was observed that data from some loggers had a greater scatter of position points over a short time interval than data from other loggers. To test whether error was being introduced to the precision of data by the data loggers, MKIIA and MKIIB GPS data loggers were installed side by side in a stationary position for a period of 4 hours. The loggers were set to record position at 10 second intervals and the point data were projected in WGS84 UTM Zone 55S using ESRI ArcMap 9.2 (see Figure 6).

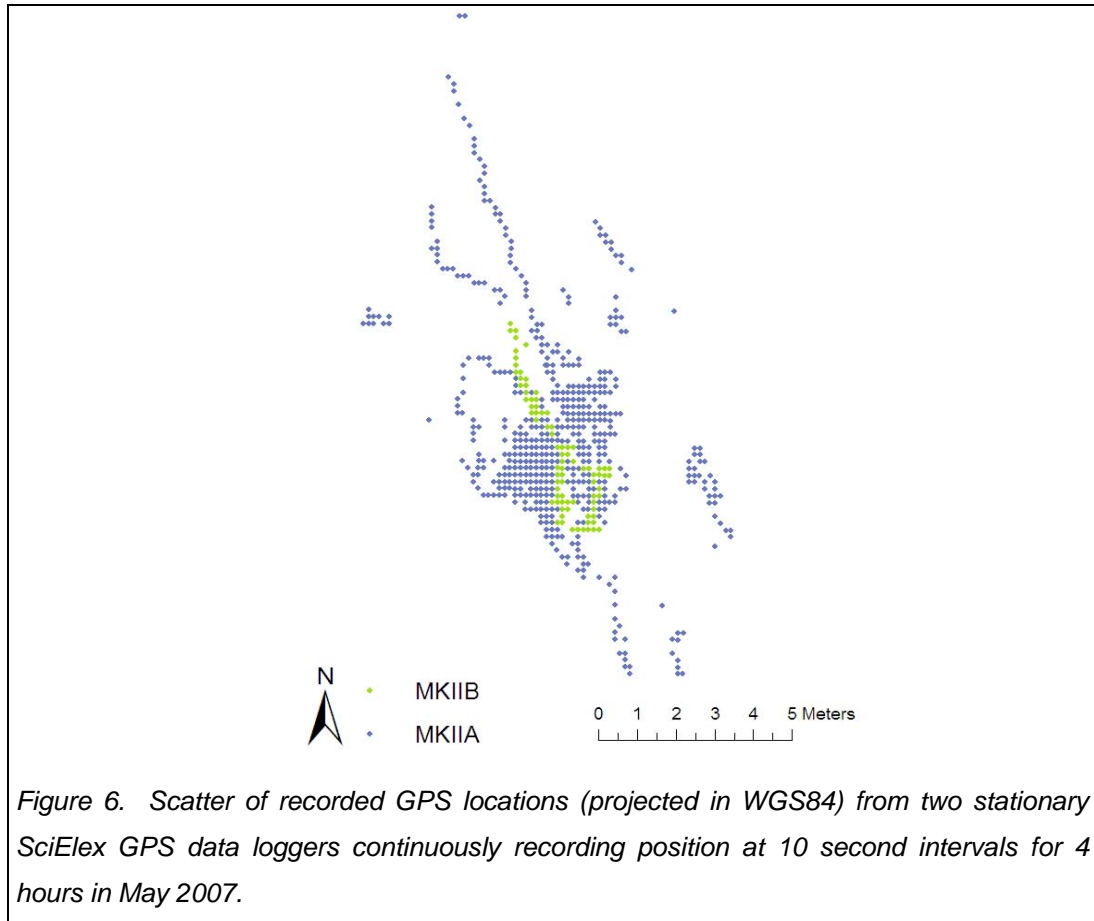


Figure 6. Scatter of recorded GPS locations (projected in WGS84) from two stationary SciElex GPS data loggers continuously recording position at 10 second intervals for 4 hours in May 2007.

The MKIIA logger had a very wide scatter of points with a Root Mean Square error (RMSE) of 18.6 metres difference between the most distant recorded points. The MKIIA logger was a pilot version of the Mark II logger and used a different GPS receiver to the production model (MKIIB). The scatter of points for the MKIIB logger was within the expected range of precision for this type of GPS receiver (less than 6 meters in total range). Enquiry to the manufacturer of the data loggers identified the source of error as the type of GPS receiver installed in the MKIIA loggers (Verdouw 2007). The manufacturers corrected this error in MKIIB and later releases of the software and loggers by using a different type of GPS receiver. Only 2 of the MKIIA GPS data loggers were produced and these loggers were subsequently upgraded with Fastrax uPatch100-S GPS receivers. Data collected by MKIIA loggers were flagged in the database and not incorporated in the dataset compiled for analysis in this study.

2.2.4 Identifying fishing events in the GPS data stream

In the Tasmanian abalone fishery, vessel speed is usually less than 2 knots while the diver is in the water (Mundy 2007) so for this study the speed of a vessel was a

reasonable indicator of when fishing activity occurred. Initially the GPS data stream was filtered or colour coded by speed to identify periods in the datastream where and when the vessel was travelling slowly enough for a diver on surface-supply air to be in the water. However, this simple approach did not distinguish between a vessel travelling slowly and actual dive activity. To conclusively identify dive activity, 'waypoint' buttons were developed on MK0 and MKI GPS loggers for the divers or deckhands to flag in the datastream the time and location where the diver entered and exited from a dive. This solution was only partially successful, as frequently the diver or deckhand would forget to push the entry or exit waypoint button, or the deckhand would be occupied with controlling the vessel and looking after the diver. At the end of the early trials, it became apparent that an automated system for recording entry/exit from a dive was required.

2.3 Depth/Temperature Logger

An automatic system to record entry and exit of a diver from the water was necessary for accurate identification of the start and end points of fishing events in the GPS datastream, to identify locations where fishing occurred. This information was recorded by the dive computers of abalone divers. However:

- some abalone divers did not use dive computers;
- a wide range of dive computers was in use, all recording different types of data;
- it was prohibitively difficult to ensure that dive computer time settings were accurate.

Using data from dive computers was not considered a viable option. An alternative to dive computers was a basic depth/time recorder such as those used to record seal and penguin foraging and diving behaviour (Lea *et al.* 2002, Charrassin *et al.* 2004). As well as identifying sections of a GPS datastream when fishing occurred, depth and temperature loggers precisely and accurately recorded the amount of time spent fishing on a day. This information was important for fishery assessment. In traditional stock assessment of the Tasmanian abalone fishery, effort (duration of diving per day, in hours) was estimated by the diver at the end of the day and reported to the Department of Primary Industries and Water (DPIW) with abalone catch figures using a paper docket system (Tarbath *et al.* 2007). The reporting requirements did not specify a precise measure of time. Consequently, dive time estimates were often rounded by divers to the nearest half hour or full hour (Mundy 2006a). Depth and temperature loggers provided a more accurate measure of

diver effort. All divers participating in the study who were issued with a GPS receiver/data logger were also issued with a depth and temperature logger.

2.3.1 Design and Specifications

The depth and temperature recorders used in the TAFI data collection program were produced by a Canadian company, Reefnet (www.reefnet.ca). The small loggers recorded depth (pressure), temperature (degrees K), and time (with an internal crystal clock counter). Data were obtained using both SensusPro and SensusPro Ultra models of depth loggers (see Table 1 for depth logger specifications). Solid state flash memory in the loggers would fill to capacity before old data were overwritten. The sensors and logger were housed in a polycarbonate case and were attached to a diver's vest with a Velcro tab strip or stainless steel ring (Figure 7). Data were downloaded using a dedicated download serial interface download cradle.

Table 1. Specifications of ReefNet depth and temperature loggers (ReefNet 2002b).

Logger	Projected battery life	Memory	Accuracy of depth sensors	Accuracy of temperature sensors
SensusPro	2 - 5 years	100 Dive Hrs (@10sec)	+/- 0.3048 m (resolution of 1.27 cm of water)	+/- 0.8 C (resolution of 0.01 C)
SensusPro Ultra	2 - 5 years	1500 Dive Hrs (@10sec)	+/- 0.3048 m (resolution of 1.27 cm of water)	+/- 0.8 C (resolution of 0.01 C)

The 'Ultra' model loggers, with greater data storage capacity than the SensusPro loggers, began to be produced part-way through the data collection program and were immediately adopted. The greater memory reduced the likelihood of data loss, through overwriting, which was a hazard that had been identified while using the SensusPro model. Data were downloaded at irregular time intervals when convenient for divers, though data had to be downloaded frequently enough to capture data records before they were overwritten.



Figure 7. A SensusPro depth and temperature logger, here attached to a diver's equipment. The loggers turned on and off automatically when the diver entered and left the water. Credit: TAFI Abalone Group Image Collection, 2007.

The depth and temperature loggers had delayed automatic on/off switches. The loggers turned on when immersed below 0.914 m for longer than 150 seconds (at a 10 sec sampling interval) and back off again after 150 seconds above 0.914 m. Reefnet provided a software interface to download, manage and export data from the loggers. Depth logger sampling frequency was set using this interface. The SensusPro loggers were set to record depth (pressure), temperature and time at 10 second intervals, matching the sampling frequency of GPS data loggers.

2.3.2 Clock Drift in Depth Loggers

SensusPro depth loggers did not log real time data. Instead, the internal clock functioned as a timer. At the moment of power-up during manufacture, the clock commenced counting. When loggers detected a change in pressure above a given threshold (indicating that the logger was underwater), the clock count (in seconds since power up) was recorded. When data were downloaded from the loggers to a computer that had been synchronised to NMEA time, the real time at download and logger clock count at download were recorded in the download data file. ReefNet software calculated the real time at the start of a dive and a time stamp for every depth record by subtracting the difference in clock count from the real time at download (ReefNet 2002a).

Drift in the frequency of the crystal clock used in the depth loggers occurred, which is not unusual in small devices with internal crystal clocks (Serway and Jewett 2003). The manufacturer's specifications for the crystal used in the Sensus loggers is ± 20 ppm (pulses per million), which equated to an error of up to 2 seconds/day. The crystal counters in the depth loggers suffered from time drift at varying rates in

each logger. Each logger required independent calibration. Clock drift had to be calculated for each data download and a correction applied to the data prior to matching depth logger data with the GPS position data. Without correction, a disparity in boat speed and diver depth could be seen; sometimes the boat was apparently travelling very quickly when the diver was supposedly in the water.

Data were not deleted from the loggers at download so the clock drift between two downloads could be calculated by downloading the same dive on two or more occasions separated by several weeks. The accrued difference (in seconds) in the start time of a specific dive between the two download events was calculated as the clock drift for that period. Clock drift for each deployment was assumed to be linear and as a function of the number of days elapsed allowed calculation of the drift in seconds/day. Correction per second elapsed was calculated for each deployment and applied to the time/date field of the downloaded data. In applying this correction to each downloaded data set (example of corrected data shown in Figure 8), the mismatch between high boat speed and diver depths was eliminated.

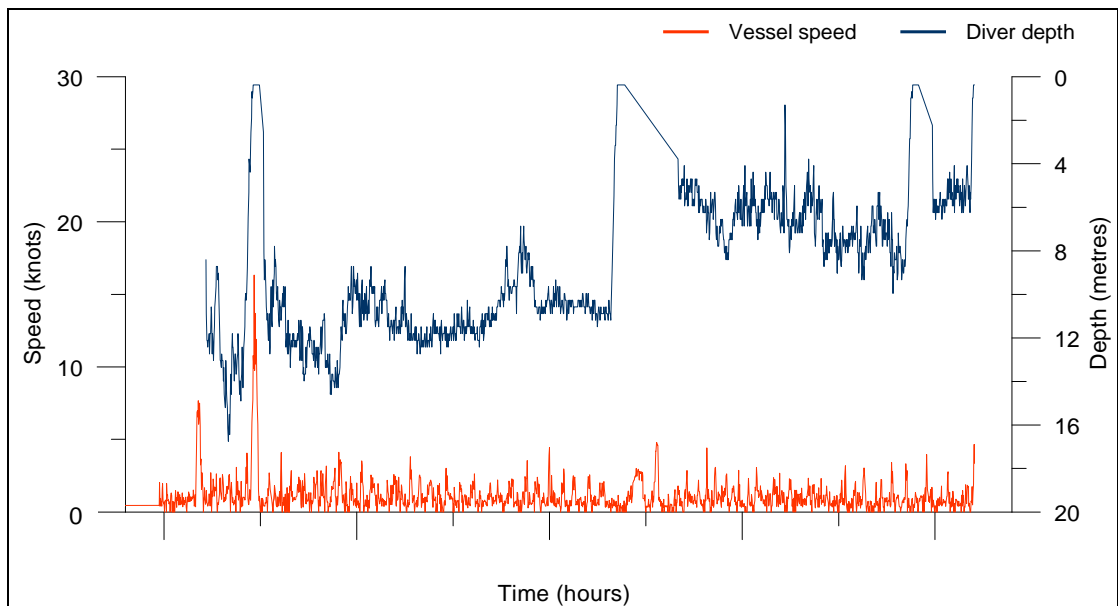


Figure 8. GPS logger and corrected depth logger data plotted for a day of fishing. Four separate fishing events were recorded by the depth logger on this day, at dive sites in close proximity to each other. Periods of time when the diver was in the water are highlighted in blue. Between the first and second dive the vessel briefly reached a speed of almost 17 knots.

2.4 Data Collection

Raw data from the GPS loggers and depth loggers were synchronised and matched in a single dataset so that depth data defined the GPS positions where fishing activity occurred. The raw data downloaded from each logger were pre-processed before the two data sets were matched.

2.4.1 Raw Data from Loggers

GPS Logger

After being turned on, the GPS loggers started recording when the integrated GPS receiver received the first positive fix from satellites. The loggers recorded receiver position at 10 second intervals until turned off again. If the GPS receivers lost reception from satellites, they did not record any more data until a valid GPS signal was received. The text files downloaded from a MKII GPS logger using manufacturer firmware contained the following fields:

- **Diver_Code:** Entered by researchers when equipment was deployed
- **Divers:** Optional, flagged if more than one diver used the logger
- **Event:** Flagged 'start/end' by the 'waypoint' buttons (see section 2.2.4)
- **UTC_time:** Position time stamp from the GPS receiver
- **UTC_date:** Position date stamp from the GPS receiver
- **Corrected_Time:** Firmware calculated time from user selected UTC zone
- **Corrected_Date:** Firmware calculated date from user selected UTC zone
- **Log_lat:** Latitude from GPS receiver
- **Log_long:** Longitude from GPS receiver
- **Speed:** Calculated by the GPS receiver, given in knots
- **Course:** Calculated by the GPS receiver

Latitude and longitude were projected to Eastings and Northings (UTM Zone 55S) using Franson Coordtrans version 3.20 software (produced by Franson technologies Sweden, <http://franson.com/coordtrans/>).

Depth Logger

SensusPro depthloggers recorded depth and temperature data as pressure (millibars) and degrees Kelvin. These data were downloaded in delimited text format. Software provided by Reefnet plotted depth and temperature data for each dive and exported a series of dives for further analysis. Output from the ReefNet export function had the following fields:

- **Index:** Sequential ID number for each dive, starting at 1 for each download
- **Device_ID :** Identification code for the logger
- **Year:** Year in 4 digits
- **Month:** Month in 2 digits
- **Day:** Day in 2 digits
- **Hour:** Hour in 24 hour time
- **Minute:** Minutes
- **Second:** Seconds
- **Offset:** Seconds elapsed since start of dive
- **Pressure:** Pressure in millibars
- **Temperature:** Temperature in degrees Kelvin

2.4.2 Matching GPS and Depth Data Streams

Data streams from the two loggers were downloaded and pre-processed separately. Pre-processing included correcting for clock drift as described in section 2.3.2 and, if necessary due to daylight savings, for changes in time zone. Time fields from both GPS and depth loggers were rounded to the nearest 10 seconds and mapped to each other on the date/time fields from each dataset. GPS data were used as the base dataset, with time-corrected depth logger data matched record for record. Output was a table with four attributes: Easting, Northing, depth and time for each point location. This table was the data source for all GIS analyses in this study. All data processing was conducted in Microsoft Access 2003.

2.4.3 Compiling a Dataset for Spatial Analysis

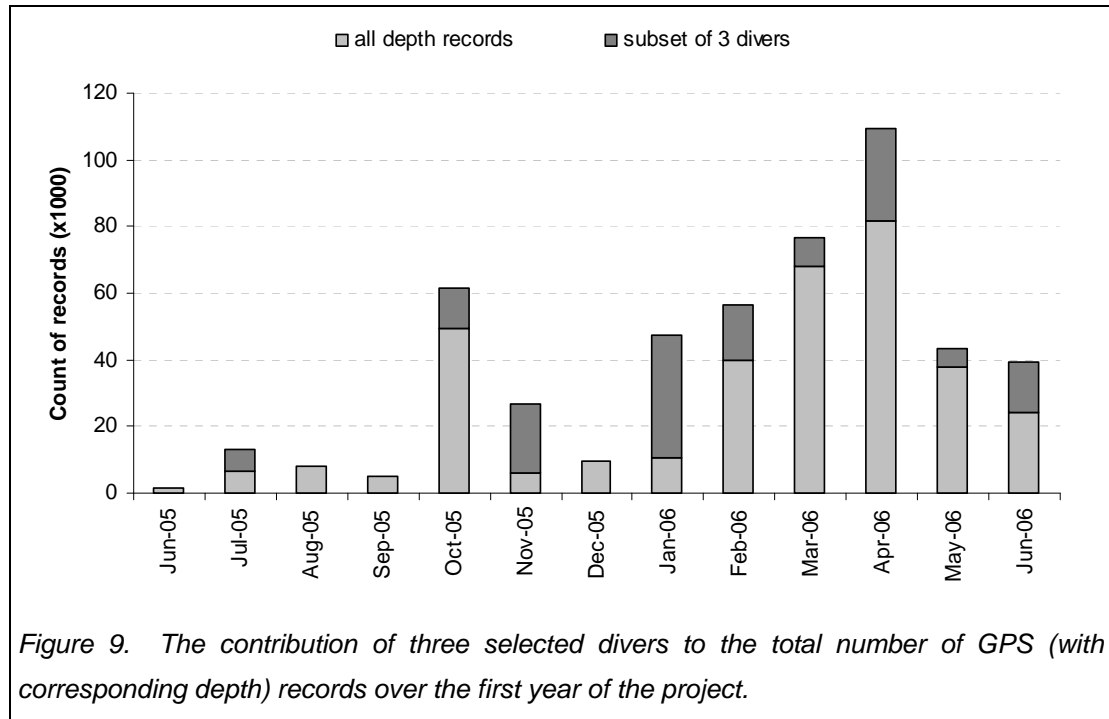
By February 2007, more than one million records of GPS position had been collected from 22 divers participating in the TAFI study. Of these GPS records, one third had corresponding depth records showing locations of fishing activity.

Of the full TAFI dataset, data from three divers were chosen for analysis (Figure 9 and Table 2). A number of criteria were used to select these divers:

- Duration of diver participation in the project
- Amount of fishing activity recorded
- Region of fishing activity

Divers with a long time series of data were considered, so that trends in spatial measures over time could be examined. In addition, divers who had spent significant time fishing were considered, in order to provide a large dataset to work

with. Finally, the fishing activity of the divers needed to overlap spatially so that between diver differences in fishing effort in the same location could be investigated.



Analyses in this study focused on the fine scale attribution of abalone catch rate, fine scale spatial movement of abalone fishing vessels during fishing activity and the distribution of fishing activity around Tasmania. These topics involved investigation of the location of fishing activity and not movement between fishing locations. For this reason, the dataset compiled for spatial analysis contains only GPS position records created during fishing activity, defined using depth logger data.

Discrete dives, or fishing events, were identified within the GPS fishing activity dataset. For the purpose of defining periods of fishing activity and single fishing events, a diver was considered to be 'fishing' when depth logger depth was $>0.5\text{m}$. After the logger had turned on (the automatic on/off switch is described in Section 2.3.1) diver was considered to have entered the water when diver depth reached $>0.5\text{m}$ and to have left the water when diver depth reached $<0.5\text{m}$. The subset of data for a fishing event incorporated all vessel positions and depth data for a single diver between entry and exit from the water. An identification code was assigned to

each individual fishing event. The total number of fishing events that were identified for each diver in each month of the study is shown in Table 2.

Table 2. The total number of 10 second fishing records for each of the three divers A, B and C, also, the number of defined individual fishing ‘events’ for each diver in each month.

Month	Number of fishing records / fishing events					
	Diver A		Diver B		Diver C	
Jul-05	6299	15				
Oct-05	12036	33				
Nov-05	594	4	11669	32	8511	20
Jan-06	6640	26	15795	38	14514	55
Feb-06	4511	17	4288	13	8170	21
Mar-06			2194	8	6671	21
Apr-06	4078	17	6988	17	16733	45
May-06	1988	8	3629	10		
Jun-06	6081	13			9164	13
Jul-06	3329	11	16258	45	8517	21
Aug-06	7102	26	4998	9		
Sep-06			13253	46	10489	23
Oct-06	6808	24	13242	36	9886	26
Nov-06	3425	13	7109	19		
Dec-06	2809	8	12712	36		
Jan-07			10932	28	16339	51
Feb-07			7618	20		
Mar-07	3864	14	13201	34		
Apr-07			13207	46	10208	27
Total	69564	229	157063	437	119202	323

2.5 Discussion of Data Collection Methods

There has been little precedent for the collection of fine scale spatial data in small vessel fisheries and in an abalone fishery it is a novel undertaking. At the commencement of this study there were no suitable, commercially available but inexpensive GPS data loggers. Hardware and data collection techniques had to be designed specifically for the TAFI project⁵. During this study the methods of data

⁵ Since 2006 a commercial manufacturing industry for GPS data loggers has blossomed, e.g. through the development of geotagging of digital photographs. In 2009, complete micro boards containing a GPS receiver, data logger & 8 MB of ram were available for <US\$50.

collection underwent continual development and refinement. As with many new applications of technology there were repeated iterations of equipment design, manufacture, deployment, feedback, assessment and redesign. A number of problems with early data collection methods are identified and discussed here.

2.5.1 Hardware problems

GPS Logger

The GPS loggers that were designed for this project were tested in the laboratory, prior to use in the field. However, significant problems were encountered during field trials and led to some loss of data. In MKI GPS loggers the power supply was not integrated into the units. External 12V batteries were often not protected from salt water and suffered from corrosion. Also, it appeared to be inconvenient for divers and deckhands to install the batteries and keep them charged. Some MKI loggers were wired into the vessel power supply and suffered from similar corrosion problems. MKI loggers sometimes stopped working after a short period of deployment, or worked infrequently and unreliably. This problem was remedied in MKII loggers when the power supply was incorporated within the units.

Depth Logger

Clock drift of up to 2 seconds per day in each depth logger complicated the data compilation process. As described in section 2.3.2, correction for drift was calculated for each logger at each data download. This was not an automated process and was time consuming though vital. A standard protocol of flagging anchor records, which can be used for calculating drift, should be developed for this part of the data preparation process. Preferably, correction for clock drift would be automated.

2.5.2 Hardware deployment and user-related problems

GPS Logger

Some errors in GPS data were recorded with the GPS loggers because of poor reception. GPS receivers need to be in a location where they can receive an unimpeded signal from satellites. Some divers installed the GPS receiver and logger in sheltered areas of their vessels where they were protected from exposure

and didn't obstruct work, but this resulted in unreliable GPS signal reception. When satellite reception was poor then the accuracy of positions recorded by the logger was reduced. Poor satellite reception was also encountered when divers fished in sheltered sections of coastline, for example, near a steep cliff. Typically, error due to poor reception was seen as sudden uni-directional and rapid apparent movement of a vessel during a fishing event, sometimes over land, followed by a sudden reversion to the previous location when good reception was restored.

When noticed during processing, these errors were removed manually from the dataset. The elimination process could not be automated. Some GPS loggers keep a record of the number of satellite signals they receive at each position (Rogers *et al.* 2004, Burns and Castellini 2006). If these pieces of information were recorded by the SciElex GPS loggers, then they could be used to flag potentially erroneous positions and to eliminate them automatically from the dataset. Problems with the location of installation of GPS loggers on boats were identified in the data set during the data collection program and resolved by talking with individual divers about appropriate places to install GPS loggers. Poor satellite reception is unavoidable when divers fish in sheltered areas of coastline.

At the beginning of the research project divers were asked to turn on GPS loggers when they arrived at a dive site and to turn them off again when departing a dive site in order to conserve battery power in external, MKI type batteries. However, divers occasionally forgot to turn them back on again at the commencement of the next dive and some spatial data were lost. Subsequently, divers were requested to leave the GPS data logger turned on for the entirety of each fishing trip. Some divers started to do so while others continued to turn the loggers off between dives. In the future it will be interesting (although it is not the intention of this thesis) to investigate patterns of vessel movement across a whole day, both when fishing and not fishing. For this type of investigation a record of vessel movement between dive sites as well as during dive activity will be necessary.

Depth Logger

The introduction of depth loggers to this data collection program has been very valuable. Without depth loggers, identification of fishing locations would have been much more difficult.

2.5.3 The cost of multiple data formats

Large amounts of spatial data were produced through current data collection processes. However, a lot of pre-processing and data manipulation was required to construct a dataset that could be used to investigate spatial dynamics in the Tasmanian abalone fishery. Different formats of output from data loggers necessitated a lot of processing to bring together datasets from different divers, and some data collected early in the project were unsuitable for analysis. The database used for collation and processing of data went through several iterations. With the experience gathered to date to guide protocols and database development, data processing will, in the future, be more streamlined. An alternative database that simplifies many of these required processes has been designed by TAFI staff for long term collection of data for the TAFI project..

CHAPTER 3 SPATIAL DATA AND FISHING EFFORT ANALYSIS

3.1 Introduction

3.1.1 Catch Rates as a Measure of Fishery Performance

The catch rate measure currently used in the Tasmanian abalone fishery is the same Catch Per Unit of Effort (CPUE) index used in fishery assessments worldwide. Fisheries assessed using some measure of catch per unit of effort are as disparate as pelagic long line fisheries, trap-based crustacean fisheries, trawl fisheries and mollusc dredge fisheries (Hilborn *et al.* 1995). For a single fishing event, effort should ideally be calculated as the product of the fishing power and the amount of time spent fishing (Beverton and Holt 1957). A range of different measures of fishing power exists, usually relating to amount of fishing gear used. Measures can include the number of hooks on a long line, e.g. pelagic fisheries (Bigelow and Boggs 1999), trawl net capacity and vessel speed, e.g. prawn fisheries (Dichmont *et al.* 2003) and number of pots set e.g. cod fishery in New Zealand (Cole *et al.* 2004). For the Tasmanian abalone fishery, fishing effort has been calculated simply as the number of hours spent fishing by a single diver (Tarbath *et al.* 2007), with 'hours' estimated by each diver (such estimates can be inaccurate).

When using CPUE as an index of abundance in fisheries management, the following relationship is assumed (Haddon 2001):

$$C/E = qN \qquad \text{Eq. 1}$$

Where C is the amount of catch taken, E represents effort, q represents catchability and N is the unknown abundance of fish. This relationship means that catch rates should provide a performance measure for each fishery by providing information about the stock size through time. Hypothetically, a change in CPUE would be linearly proportional to a change in abundance but this is rarely the case in practice. CPUE in different fisheries can exhibit both hyperstability, where it can remain high even when stocks are low, e.g. the case of the Californian abalone fishery (Karpov *et al.* 2000) or hyperdepletion, where it appears low even when stocks are high

(Harley *et al.* 2001). Fisheries scientists have been questioning the applicability of CPUE for many years because fishers will redistribute effort to maximise profitability, rather than fishing randomly or evenly over the extent of a fishery. Radovich (1976 p32) commented that “If we were starting out now to design a survey to determine the abundance of fish off the coast, we would have a difficult time to design a more biased sampling scheme than one using catch-per-effort from the commercial fishery”. It is widely agreed that changes in the spatial distribution of either fish (i.e. migration) or fishing effort will affect CPUE independently of abundance (Bordalo-Machado 2006). Therefore, it is vital to know the fine scale spatial dynamics of a fishery before interpreting CPUE as an abundance index.

3.1.2 Abalone abundance vs. abalone availability

Abalone are benthic molluscs confined to reef and rocky habitat and typically their movement is limited to a few tens of metres per year (Morgan and Shepherd 2006). As abalone populations do not migrate, the spatial distribution of the target animal does not fluctuate, except under external influences such as habitat change, fishing pressure (Hobday *et al.* 2001) or disease, e.g. Victorian cases of Abalone Virus Ganglioneuritis (Hills 2007). However, abalone abundance does not necessarily equate to availability of abalone to the fishery. Small, juvenile abalone are cryptic until approximately 5 years of age (Prince and Hilborn 1998) and larger juveniles and sub-adults in the Tasmanian fishery are protected from fishing pressure by minimum legal lengths (Tarbath *et al.* 2007). Animals smaller than the legal size limit are not available to divers and are not part of the ‘abundance’ that is measured using CPUE. In some populations, a greater proportion of abalone never reach the imposed size limit due to local conditions limiting growth (Morgan and Shepherd 2006) and these abalone are also not available to divers despite being locally highly abundant. Also importantly, habitat complexity influences the “sightability” of abalone and therefore availability of abalone to fishers. In the case of abalone fisheries it is important to make the distinction between CPUE as an index of abundance and CPUE as an index of availability.

3.1.3 CPUE as an index of availability

In Tasmania, CPUE has been found to provide valid information about stock status under some circumstances, i.e. when the fishery is performing very well and when it is performing very badly (Tarbath *et al.* 2005). Tasmanian abalone fishery assessment reports have shown that the east and west coasts typically have

different catch rates (Tarbath *et al.* 2005, 2007). However, because catch and effort data are usually collected at spatial scales much coarser than the spatial scale at which fishing occurs, simple summary catch rates from abalone fisheries do not necessarily represent what is happening at the spatial scale of stock distribution and are flawed as a fishery performance measure. For abalone, the key problem with using catch rate as a performance measure is that it is susceptible to hyperstability. Through behavioural changes, divers may maintain high catch rates while depleting a stock (Karpov *et al.* 2000). In addition, localised depletions would not be detectable using catch rates aggregated across the current management blocks (Prince 2005). CPUE is currently applied as an index of abalone availability in the Tasmanian abalone fishery at an inappropriate spatial scale.

Spatial measures of effort

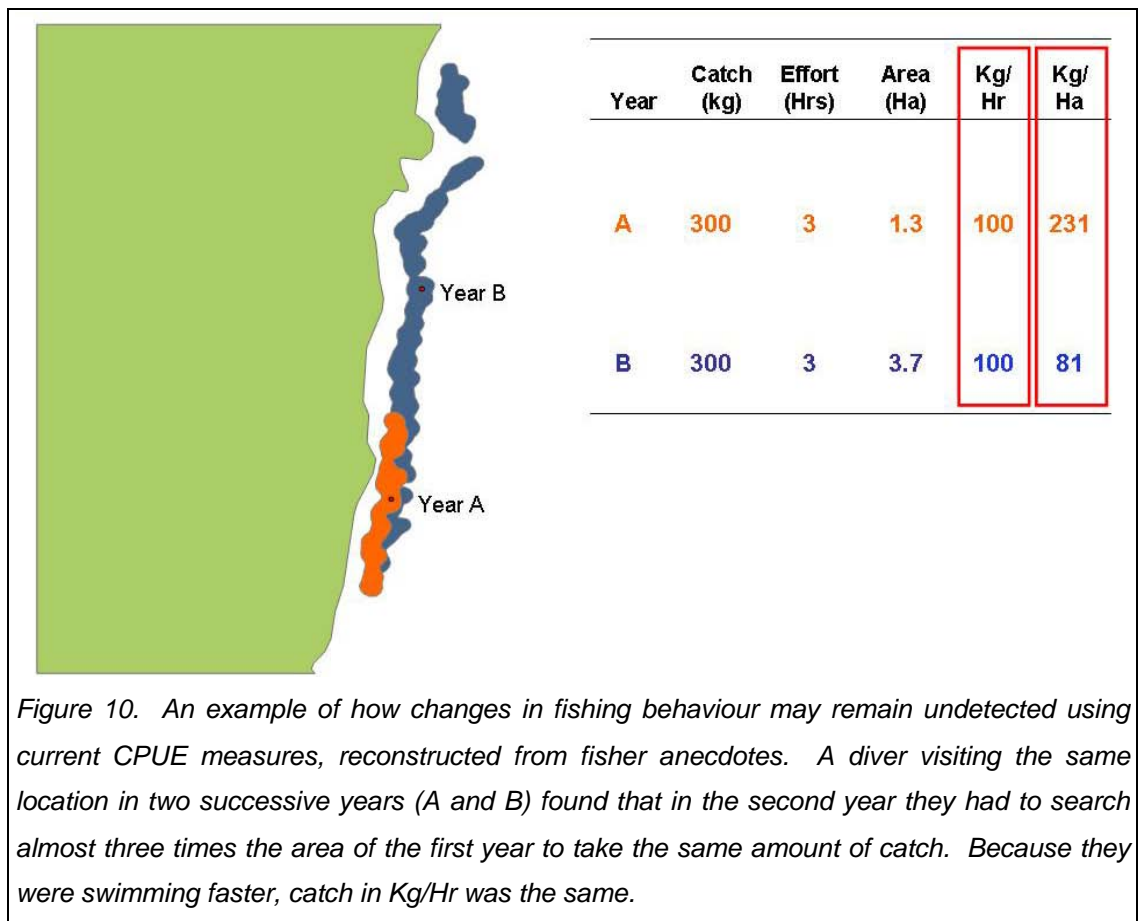
In some fisheries, the measurement of effort used in calculating CPUE has a spatial component. In trawl fisheries, for example, effort is calculated as a product of time, speed and gear units (effectively the area fished in a unit of time) (Buckworth 1985, Bishop *et al.* 2004). There is no similar measure of volume, area or distance used to calculate effort in the Tasmanian abalone dive fishery. Anecdotal evidence suggests that such a measure is needed (Mundy 2006b). For example catch rate, can remain stable while the amount of area searched changes (Figure 10). If a diver needs to search an area almost three times as large as a previous year to maintain the same catch rate in the same location, and in the same number of hours, then although search area has increased, the catch rate (as catch per hour) remains the same and a decline in abalone density is not detected.

A summary of the problems

Some identified problems with the way that CPUE is calculated and applied as an index of abundance in the Tasmanian abalone fishery are:

- a. Effort is measured in hours and is reported by a diver at the end of the day. These reports are often based on estimates and can be quite inaccurate.
- b. Effort and catch are pooled across divers for each day of diving, and reported within large geographic areas, which obscure fine scale variation and changes in CPUE.
- c. Effort is measured only as time and the amount of area searched by a diver is not taken into account, i.e. there is no spatial measure of effort.

Raw CPUE may never be a precise index of abalone abundance. However, in the absence of validated alternative performance measures, CPUE data will continue to be used to inform fishery management advice. Despite some limitations, CPUE is a valuable index to assess the abundance of abalone. Standardised fishery CPUE estimates have been shown to be more informative than non-standardised CPUE (Maunder and Punt 2004). However, where consistent effort is applied to a fishery, unstandardised CPUE may still be a useful measure (Tarbath *et al.* 2005). Assessments of abalone fisheries in New South Wales, Western Australia and South Australia also use CPUE data as performance indicators. (Worthington *et al.* 1998, Chick *et al.* 2008, Hart *et al.* 2009). If standardised CPUE estimates can be generated at fine spatial and temporal scales this may allow fishery managers to use fishery dependent data with much greater confidence.



3.1.4 Objectives

My objectives in this chapter are to address each of the three problems raised above using fine-scale data on the temporal and spatial distribution of fishing

activity (collection methods described in Chapter 2). Overall, this chapter aims to test the value of alternative measures of fishing effort developed from fine-scale information about divers' behaviour 1) to complement traditional time-based estimates of CPUE, and 2) to capture the complexity of individual divers' behaviour.

- Firstly, I test the value of accurately recording the duration of fishing for improving current estimates of daily CPUE (Catch/hour of fishing) to answer the following questions:
 - Is there is a significant difference between estimates of fishing time as reported by divers and the duration of fishing events as recorded by data loggers?
 - If so, does this error significantly affect daily time-based CPUE measures?
- Secondly, I use GPS-sampled vessel coordinates to i) record vessel movement, ii) use different GIS techniques to estimate the amount of area potentially searched by a diver while fishing, and iii) develop some spatial daily catch rates (i.e., distance-based rates expressed as catch/km of vessel track, or area-based expressed as catch/ha searched by a diver.
 - Can these alternative indices (distance-based or area-based) of fishing effort provide original and useful information about fishing effort in complement to traditional time-based CPUE?
 - Additionally, can distance-based and area-based indices of fishing effort capture differences in individual divers' fishing behaviour?
- To illustrate the value of the proposed techniques, in the last section of this chapter, I apply fine-scale daily CPUE and spatial catch rates to a specific case study.

3.2 Methods

The data collected for this study encompassed much of the fishing activity of three commercial divers who were active in the Tasmanian abalone fishery between July 2005 and April 2007 (see Chapter 2). As part of the fishery-wide catch reporting requirements, these divers recorded abalone catch for each day of fishing activity. These catch data were made available by Tasmanian State Government fisheries managers for the purpose of this study. The amount of catch taken on each separate dive was not recorded by divers so CPUE could only be calculated for

each full day of diving activity and not for each dive. The spatial resolution of CPUE estimates was limited by the temporal resolution of catch reporting.

3.2.1 Measuring Time: Do accurate measures of dive duration improve CPUE estimates?

Duration of fishing activity

The amount of time elapsed during each fishing event was calculated from depth logger data. As described in Chapter 2, a ‘fishing event’ began after the logger had turned on and included all time when the diver was below 0.5 metres. It ended when the diver rose above 0.5 metres. Total time spent fishing was calculated for three separate divers, Divers A, B and C, for each day of fishing activity recorded between July 2005 and April 2007. The duration of all fishing events from one day for one diver were summed to provide the total amount of time the diver spent fishing on that day. The day total duration of fishing, calculated from depth logger data, was plotted against duration of fishing as estimated and reported by the divers in the Department of Primary Industry and Water (DPIW) abalone diver’s docket books.

Daily CPUE

Two different values of CPUE were calculated and compared in order to discover whether catch rates calculated using diver estimates of effort (hours spent fishing) were different to catch rates calculated using more accurate depth logger derived measures of effort (hours spent fishing). CPUE was calculated for whole days (dictated by the temporal scale of catch reporting). Daily catch per hour using the logger-derived duration of fishing ($CPUE_{dl}$) was calculated for divers A, B and C as:

$$CPUE_{dl} = kg / Hour_{dl} \quad \text{Eq. 2}$$

And using the diver estimated duration of fishing ($CPUE_{diver}$) as:

$$CPUE_{diver} = kg / Hour_{diver} \quad \text{Eq. 3}$$

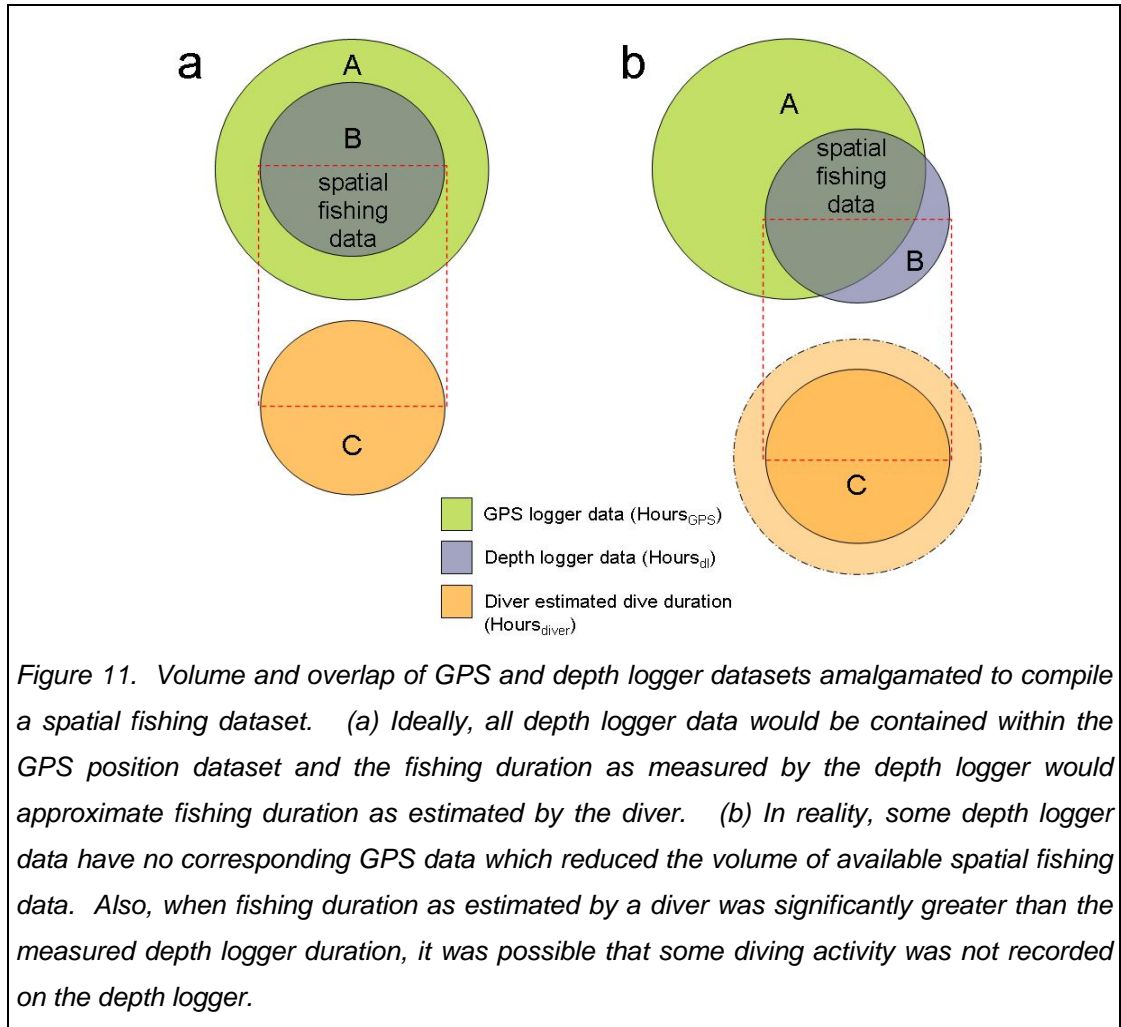
Where kg is the daily catch in kilograms. The CPUE calculated using each method was plotted. A Two-way ANOVA with repeated measures ($CPUE_{dl}$ and $CPUE_{diver}$) was used to investigate whether there were significant differences between the two methods and between individual divers (A, B or C) on the mean CPUE values.

Diver estimated CPUE ($CPUE_{diver}$) was also compared with logger estimated CPUE ($CPUE_{dl}$) using simple linear regression across all fishers and for each diver. An analysis of covariance (ANCOVA) was performed between $CPUE_{dl}$ and $CPUE_{diver}$ with individual diver (A, B and C) as a cofactor to investigate whether individual errors in time reporting had a significant effect on CPUE values with the two methods.

3.2.2 Selecting Days for Spatial Catch Rate Analyses

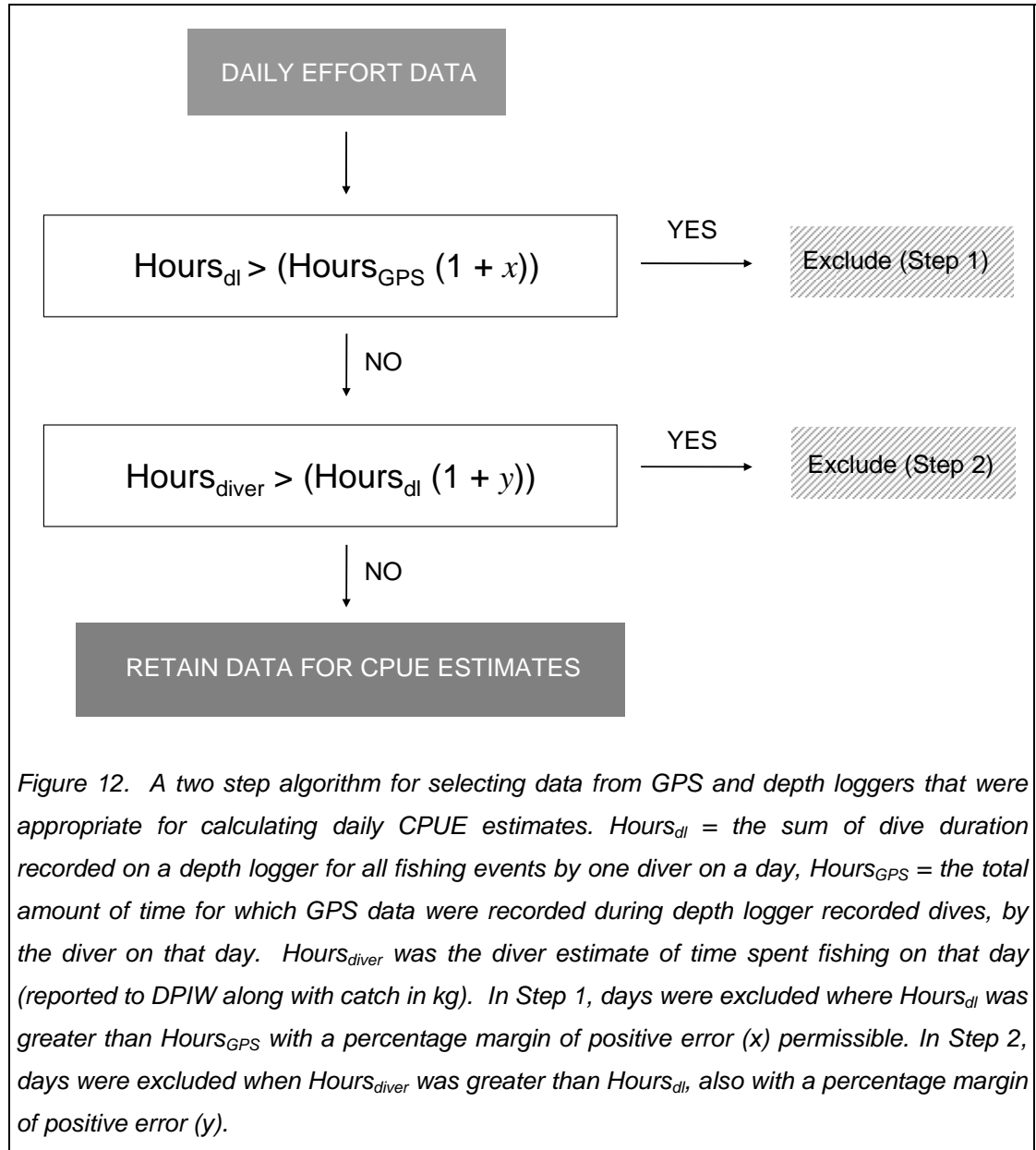
Daily abalone catch in kilograms was reported to the Tasmanian DPIW by each diver. This record of abalone catch was only available daily, even when complementary GPS and depth data were collected at very fine temporal and spatial scales using the loggers described in Chapter 2.

The equipment and techniques used in this study were innovative, and new to the divers who participated. On some days the depth loggers and GPS units were not deployed by divers during all dives, or did not function properly during all dives, particularly at the beginning of the study. As a result, on some days the daily catch in kg included abalone collected on dives for which no spatial (GPS) fishing data were recorded (Figure 11). It was necessary to identify these days and exclude them from the spatial catch rate analyses.



An algorithm for accepting effort data from loggers

A two-step algorithm of data filtering was employed to exclude days of fishing when there were missing GPS or depth log data. The algorithm was employed to identify large discrepancies in fishing event duration between either (a) GPS and depth loggers, or (b) depth loggers and information reported by divers (Figure 12). In instance (a) there were depth records to indicate fishing activity but no corresponding GPS data. In instance (b) diver estimates of fishing duration were much greater than the duration recorded by the depth logger. This could have been human error in reporting but also could have been fishing activity that was not logged on the depth logger.



To assign the margin of error (x) to be allocated in Step 1, $Hours_{dl}$ and $Hours_{GPS}$ for each diver on each day of fishing were compared. The total number of recorded minutes of fishing that missed valid spatial data was calculated as the disparity for each dive between $Hours_{dl}$ and $Hours_{GPS}$, summed for each diver and day of fishing. Distribution across fishing days was plotted in minutes with 10 minute bins in order to look at the amount of disparity for each diver and assess whether the distribution of disparity was different for each diver.

The effects of different values of x on data retention were modelled using a spreadsheet to simulate the percentage of data lost for each potential x value. $Hours_{diver}$ were plotted against $Hours_{dl}$ to help decide the value of y (margin of error

assigned in Step 2). Again, a simulation spreadsheet was used to model the number of days that would be retained in the dataset with different values of y . Where Hours_{dl} were greater than $\text{Hours}_{\text{diver}}$, the Hours_{dl} term was accepted as reliable. The discrepancy was attributed to diver estimation error although there were cases when this discrepancy was improbably large.

3.2.3 Measuring Distance: Creating a path of vessel movement

Distance travelled when searching for prey is a one-dimensional spatial measure of effort (Turchin 1998). The relationship between the distances travelled by the diver and the boat while fishing may be influenced by the weather/sea conditions because in rough water boats must remain further from rocks and shallow reefs than in calm conditions. In calm conditions a boat may sit directly above a diver but in rough water find it necessary to stay further away from the diver, staying clear of hazards by running motors and shifting position continually (Mundy 2007).

A path from data points

Vessel paths for each fishing event were inferred from point location data using the 'Convert Locations To Paths' function within *Hawth's Analysis Tools for ArcGIS* Version 3.21 (Beyer 2004) as shown in Geoprocessing Box 4 (see Appendix 1). This function uses a common method for digitising a curvilinear path, i.e. approximating it with a series of straight lines (Turchin 1998). To digitise the path of a continuously moving vessel, GPS points were connected in chronological order by straight line segments to create a single path for each fishing event as illustrated in Figure 13.

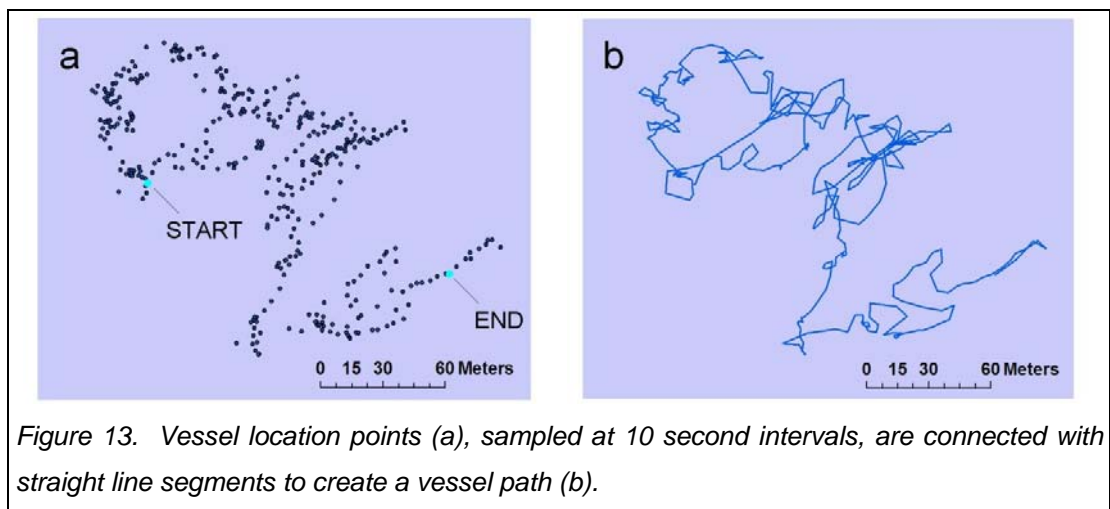


Figure 13. Vessel location points (a), sampled at 10 second intervals, are connected with straight line segments to create a vessel path (b).

The frequency distributions of daily path distance for each diver were generated and described. Paths of vessel movement were later used in buffer analyses (section 3.2.4) and fishing behaviour analyses (Chapter 4).

Daily Catch Per Unit Distance

All vessel track lengths for a day were summed to give the total distance covered during fishing by the vessel in that day, excluding travel between fishing events. Catch per kilometre of vessel track (Catch Per Unit Distance) was calculated as:

$$CPUD = kg / km \quad \text{Eq. 4}$$

Where *kg* is the daily catch in kilograms and *km* is the path length during fishing on that day in kilometres. Fishing events of different durations create paths of different lengths. The rate of movement (displacement through time) can be used to standardise these paths with respect to time, however, as distance was here used as a measure of effort in calculating CPUD, and daily catch was not standardised for duration, this was not necessary.

3.2.4 Measuring Area: An index of diver ‘search’ area

The GPS loggers used in this study captured fine scale data by recording the movement of the vessel used for fishing. Using vessel-mounted loggers meant that the movement, or track, of a diver in the water was not recorded and the amount of area searched by a diver was not measured exactly. The relationship between the search patterns of a diver and the GPS path of a vessel was unknown, though likely to be varied under a range of conditions. While the actual area searched by a diver could not be determined using the data collected, standard GIS techniques were used to calculate an estimate of the potential area utilised by the diver. This estimate functioned as an index of diver search area.

Quantifying the area searched

The amount of area available to a diver to be fished during each fishing event was estimated prior to generating a catch rate with a two dimensional spatial component (catch per unit of area searched). Three different spatial analysis techniques were

applied to the data to calculate a range of area estimates that may describe diver search area⁶. The techniques used were:

- Minimum Convex Polygon
- Buffer Analysis
- Kernel Density Analysis

Each technique was applied to data from individual fishing events to generate descriptions of area available during each event. The differences between these three measures of area search were tested using an ANOVA with repeated measures. The area estimates were used to generate daily measures of catch per unit of area (CPUA) searched. The values of CPUA from each technique were compared using an ANOVA with repeated measures.

Minimum Convex Polygons

A minimum convex polygon (MCP) represents the minimum possible area described by a convex polygon that contains a complete set of points. It can be imagined as the area contained within a rubber band if it were stretched around the outside, to contain all points in a set. Minimum Convex Polygons are frequently used to generate home range estimates (Harris *et al.* 1990, Halloran and Bekoff 2000, Haenel *et al.* 2003), although they are not considered to be accurate in estimating the use of space by an animal (Hooge *et al.* 1999, Halloran and Bekoff 2000). Using the Animal Movement tools created by Hawthorne Beyer for ArcGIS, a minimum convex polygon was generated to contain all points that the working vessel visited during each fishing event (Figure 14, Appendix 1: Geoprocessing Box 1). The area of each MCP was calculated using the 'Add Area/Perimeter Fields To Table' function within *Hawth's Analysis Tools for ArcGIS* Version 3.21 (Beyer 2004) (Appendix 1: Geoprocessing Box 2).

⁶ The "potential area searched" is to be interpreted here as the area that the diver could have sum over while looking for abalone, i.e. the potential range of places that the diver could have been in. The definition does not consider underwater visibility (which varies from day to day), field of vision, or habitat obstructions to line-of-sight.

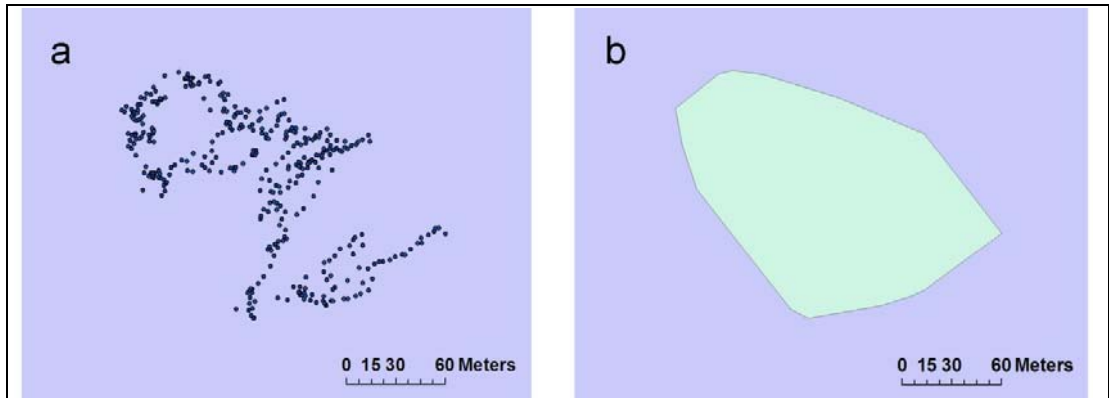


Figure 14. Vessel location points (a) for a single fishing event are contained within a Minimum Convex Polygon (b). The area of the polygon approximates the area searched by the diver.

Buffer Analysis

All divers working in the Tasmanian abalone fishery breathe surface-supply compressed air while they are fishing. Air is pumped by a low pressure compressor on the vessel to the diver through a long 10 mm diameter hose (Figure 15) and the deckhand maintains the vessel as close to the diver as weather conditions allow. Pulling a long length of hose through the water requires exertion from a diver, particularly when there is a current or strong wind at the water surface pulling the hose in a direction other than that in which the diver is moving. A deckhand will attempt to keep air hoses at a length allowing free movement of the diver but reducing drag. Generally, less than 30 m of hose will be in the water during a dive, but this is dependent on weather and sea conditions and diver preference (Mundy 2007).

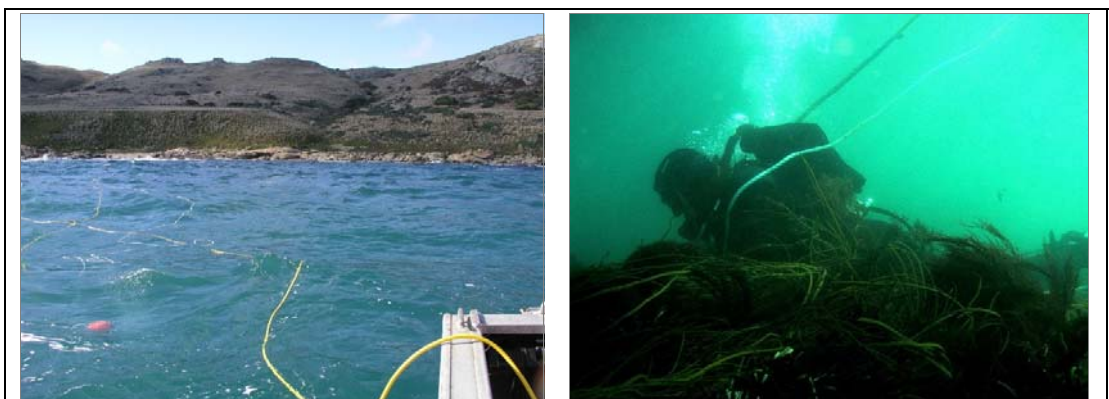
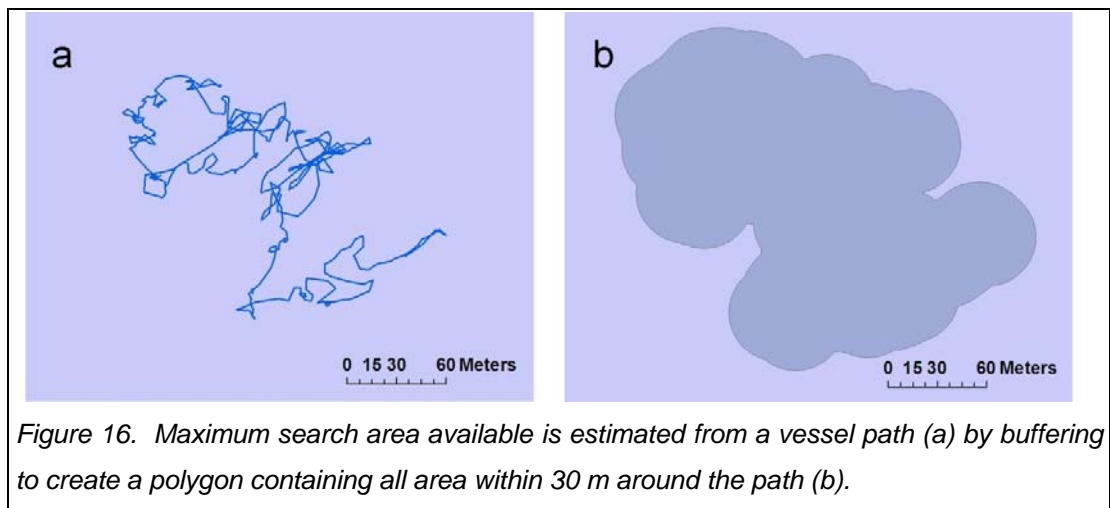
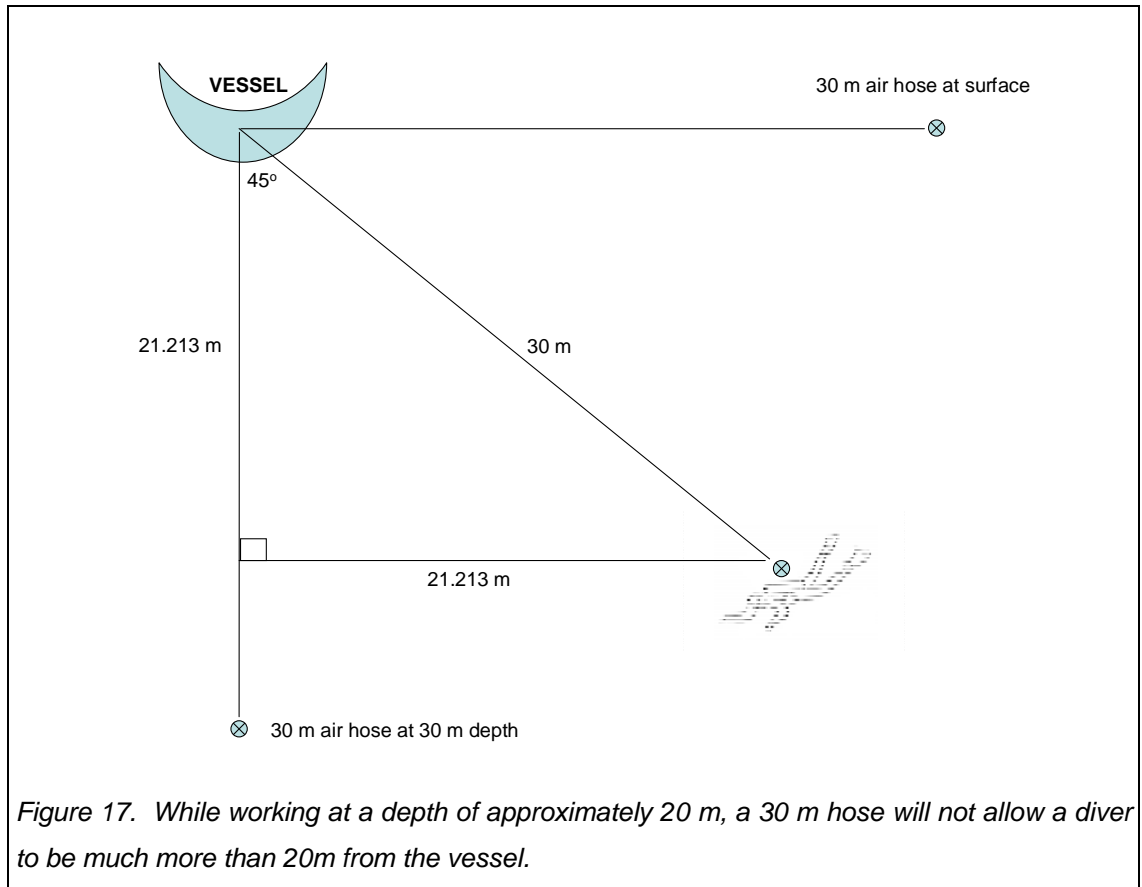


Figure 15. Divers are tethered to a vessel by the surface supply compressed air hose (yellow in these photographs). This diver is towing an orange surface buoy on a white line so that his deckhand can find him easily. Credit: TAFI Abalone Group Image Collection, 2005.

In GIS, a buffer analysis generates a polygon of defined radius around a point, collection of points or a line according to parameters outlined by the user of the GIS. A buffer analysis can be used to define the possible search area of a diver tethered to a vessel with an air hose of known length. By allowing a buffer radius of 30 m along the length of a dive track line (based on a reported average hose length of abalone divers working in the Tasmanian Fishery) the maximum possible search area of a diver can be identified (Figure 16). In reality a diver is likely to be within 30 m of the vessel for the majority of the dive. For example, while working at a depth of approximately 20 m, a 30 m hose will not allow a diver to be much more than 20 m from the vessel (Figure 17).





Kernel Density Estimation

Kernel Density Estimation (KDE) is a probabilistic technique used for estimating the home range of animals using a dataset of location points (Laver 2005). A Kernel density estimation is a non-parametric density function because it does not assume that data fit a prescribed distribution pattern, such as a circle (Selkirk and Bishop 2002). It has no shape assumption and is based on point density. Kernel density estimation allows utilisation distribution to be established by drawing contours around areas of equal density. Non-parametric methodologies are considered to be the most successful of a variety of animal home range estimators (including the MCPs described in section 3.2.4) (Worton 1989). For this reason a KDE of vessel range during each fishing event was calculated.

Deriving a KDE is a multi-step process (Hooge *et al.* 1999, Beyer 2004, Laver 2005). A defined kernel (K) is placed over each point in a dataset, weighting the area surrounding the point with values defined by the kernel function. Each point is assigned a density value based upon the proximity of the point to other points in the dataset within a defined radius. The smoothing parameter (h) describes the radius

and thus the search area around each point. A grid of defined cell size is placed over the weighted point dataset and a density value is assigned to each grid cell based upon the cumulative values of points contained in the cell. The grid surface can be contoured at specified density thresholds to give percentage density surface areas. Within GIS environments a range of tools have been developed to automatically generate kernel density grids. These tools typically offer one or more kernel types, a choice of statistically chosen or user-defined smoothing parameter (h), and a choice of default or user-defined grid cell size.

For each fishing event in the dataset, KDEs were generated in ArcView 3.2 using the Animal Movement Analysis ArcView extension (v2.04 beta) developed by P. N. Hooge (Hooge 1998). A bivariate normal density kernel was used, with a smoothing parameter, or 'bandwidth', of $h = 10$ and a grid cell size of 5 m. This combination of smoothing value and grid cell size most closely matched the scale of available data, leading to a balance between detail and resolution, i.e. not too smooth and not too many holes. The kernel density grid surface was contoured at 95% and 50% density intervals to create polygons. Each contour represents probability at a particular density, that is, the probability that the diver worked within the contour at a particular time. Within the 95% density interval there is a 95% probability that the diver was diving within that contour at any time during the fishing event. These contours are illustrated in Figure 18. The 95% contour is here used as an estimate of search area.

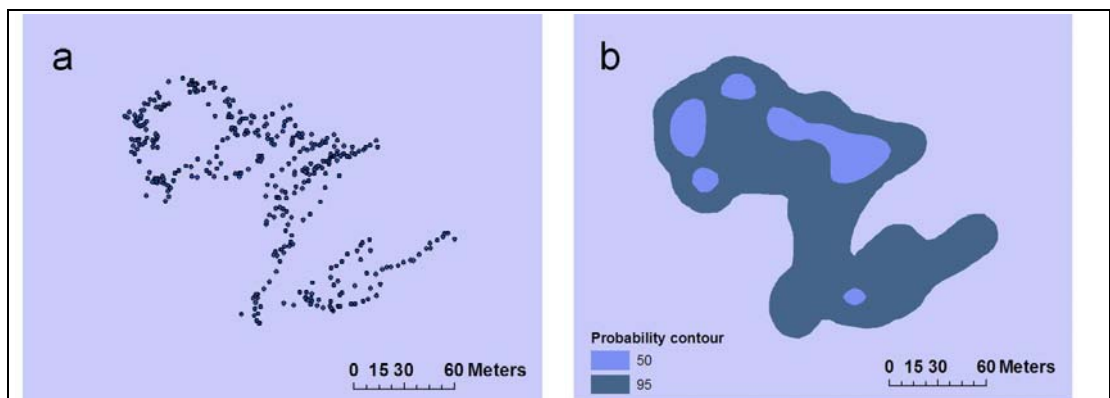


Figure 18. 95% of vessel location points (a) for a single fishing event are contained within the 95% contour of a KDE raster surface (b).

Catch Per Unit Area

Each estimate of area available to a diver in a day was used to calculate kg/ha as a Catch Per Unit of Area (CPUA) measure. For each fishing day of the year, the areas of all vessel tracks were summed to give an estimate of daily total area available to be searched by each diver, in hectares.

$$CPUA = kg / ha \qquad \text{Eq. 5}$$

Where *kg* is catch in kilograms and *ha* is the area available to be searched by each diver in hectares.

3.2.5 CPUE and CPUA at a fine spatial scale

One catch rate for multiple fishing events

In sections 3.2.1 to 3.2.4, catch rate values were calculated for each day of fishing activity. On most of these days, multiple fishing events had occurred. Three methods were considered for allocating catch rates to these fishing events:

- A. Identify the management blocks in which all fishing events for each day of fishing occurred, and allocate a catch rate to those blocks.
- B. Create a MCP (see section 3.2.4 'Minimum Convex Polygons' for methods) that encompasses all fishing events for a day of fishing, and allocate a catch rate to the polygon.
- C. Identify every fishing event that contributed to a day's catch and allocate the same catch rate (in kg/hr) to each of those individual fishing events.

The first method (A) is at the coarse spatial scale of current CPUE estimates. Method B is at a much finer spatial scale than A; each polygon encompasses all fishing events that contribute to the day's catch rate. However, the polygons also encompass area that was not fished. Method C identifies the fishing locations that contributed to a day's catch rate and doesn't include obviously unfished area. CPUE estimates are allocated to the fishery at the spatial scale of single fishing events, with mean catch rates calculated for whole days of fishing activity. Method C was chosen to allocate daily CPUE and spatial catch rates to the fishery at as fine a spatial scale as possible.

Allocating catch rates to each fishing event

The centroid location of each fishing event was mapped using ArcGIS. All fishing events that contributed to each day of fishing were assigned to the diver's catch

rate for that day. Thus, if a daily catch rate of 100 kg/hr was derived from three different dives (fishing events), then each of the three events was assigned a pooled catch rate of 100kg/hr. The centroid coordinates were linked to the $CPUE_{dl}$, CPUD, CPUA and other spatial descriptive statistics of that fishing event.

$CPUE_{dl}$, CPUD and CPUA for each fishing event were plotted on a map of the Tasmanian abalone fishery. These data can be aggregated at any spatial or temporal scale desired to deliver fishery performance measures.

Summary of catch rate indices

In this chapter, four different catch rate measures were developed for each day of fishing (Table 3). These measures were $CPUE_{diver}$, the traditional catch per hour used in management of the Tasmanian abalone fishery ($kg.hr^{-1}$); $CPUE_{dl}$, a more accurate catch per hour generated from dive logger data ($kg.hr^{-1}$); CPUD, a measure of catch per kilometre of vessel track ($kg.km^{-1}$); and CPUA, an index of catch per hectare generated from an estimate of search area available to the diver ($kg.ha^{-1}$). Separate catch rates were not generated for individual fishing events because catch data were only available for each day of fishing.

Table 3. Summary of the catch rate indices generated in chapter 3.

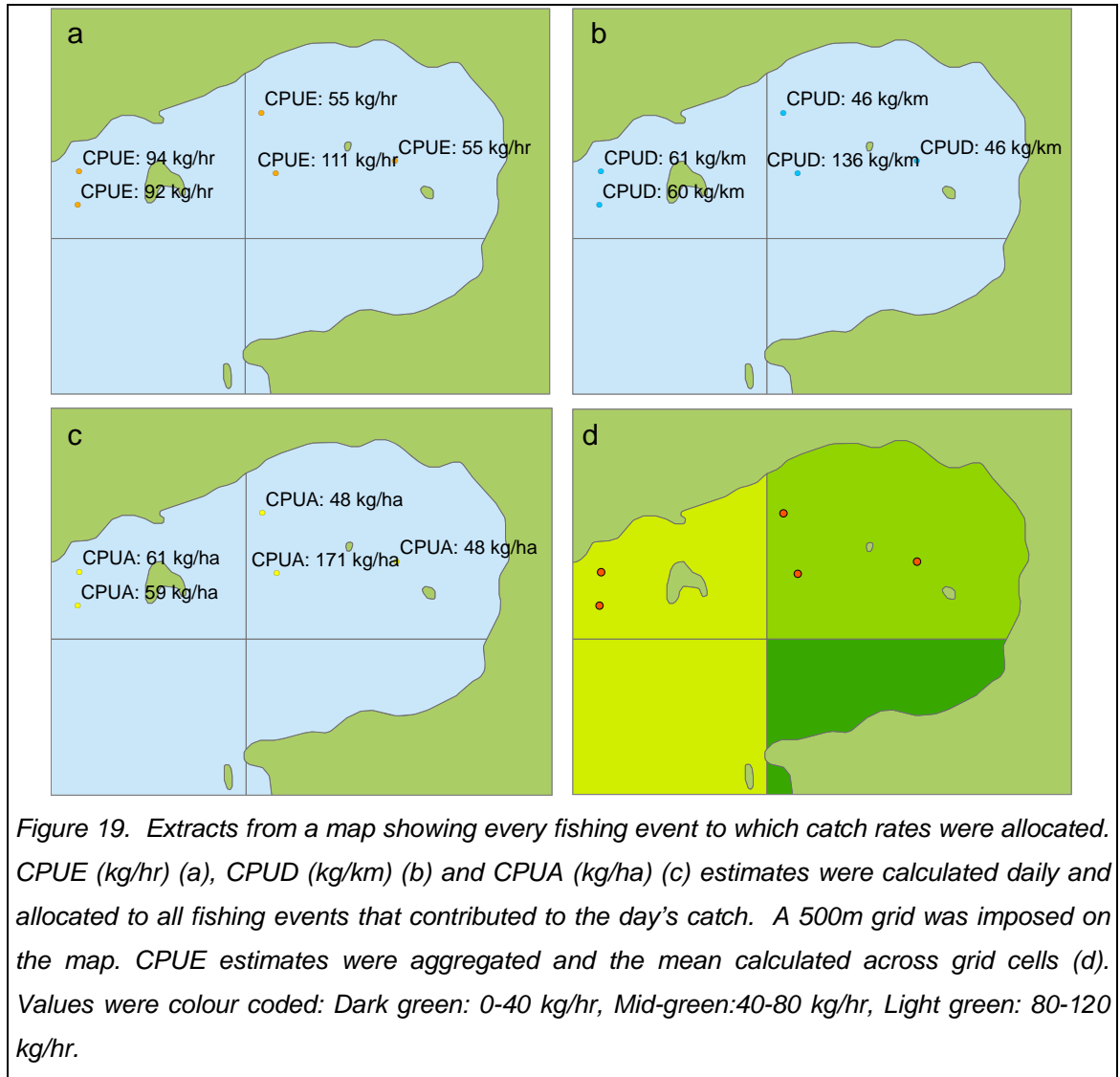
Catch Per Unit of Effort	Effort measure	Units of effort	Source	Scale of data collection	Scale of data aggregation
$CPUE_{diver}$	Time	Hours (of fishing)	Reported by diver	Day	Day
$CPUE_{dl}$	Time	Hours (of fishing)	Recorded by depth logger	Fishing Event	Day
CPUD	Distance	Kilometres (travelled)	Length of calculated vessel path	Fishing Event	Day
CPUA	Area	Hectares (potentially searched)	Contained in the 95% density contour of a kernel density estimate	Fishing Event	Day

Catch rates ($CPUE_{diver}$, $CPUE_{dl}$, CPUD and CPUA) were calculated for 149 separate days of fishing effort across all three divers (A, B and C). These catch rates were allocated to a total of 628 individual fishing events (Table 4, compare with Table 2 in Chapter 2). 64% of all fishing events recorded by Divers A, B and C between July 2005 and April 2007 were assigned catch rates.

Table 4. Catch rates calculated for each diver on each day were allocated to individual fishing events. Catch rates were assigned to 628 individual fishing events between the beginning of July 2005 and end of April 2007.

Month	Number of days with catch rates / fishing events with catch rates					
	Diver A		Diver B		Diver C	
Jul-05	4	15				
Aug-05						
Sep-05						
Oct-05						
Nov-05			6	20	5	16
Dec-05						
Jan-06	1	5	8	35	5	31
Feb-06			2	10	4	15
Mar-06			1	4	4	21
Apr-06			4	14	7	28
May-06			1	3		
Jun-06	4	13			3	6
Jul-06	1	4	10	43	4	13
Aug-06			3	8		
Sep-06			6	35	4	17
Oct-06	1	3	7	25	5	15
Nov-06			3	14		
Dec-06	2	6	5	23		
Jan-07			7	28	6	40
Feb-07			4	15		
Mar-07			9	34		
Apr-07			7	44	6	25
Total	13	46	83	355	53	227

To maintain the confidentiality of divers who have allowed us to record the locations of their fishing sites in Tasmania, a detailed fishery-wide map of CPUE distribution is not included in this thesis. Extracts from this map can be seen in Figure 19 (a) to (d). In order to mask the location of these dive sites no map coordinates or north arrow have been included in these figures. Exact diving locations can be masked by aggregating data. For the example in Figure 19 (d), data were aggregated and the mean calculated across 500m grid cells.



3.2.6. Testing the differences between the different indices: across all divers and for each diver

I applied statistical tests to the different measures of effort (e.g., duration of a fishing event, or distance covered by the vessel while fishing) and catch-rate indices (i.e., CPUE, CPUD, CPUA). Statistical tests presented in the following sections were computed using the R software (R version 2.8.1. Copyright: The R Foundation for Statistical Computing) for statistics.

Analyses of measures of fishing time ($Hours_{diver}$; $Hours_{dl}$)

Firstly, using fishing time as measured by data loggers, I focus on the effect of imprecise reporting of fishing time by diver as a source of error. To consider error in time reporting, a Two-way ANOVA was performed on fishing time estimates using

‘method’, i.e., $\text{Hours}_{\text{diver}}$ (as reported by the diver) and Hours_{dl} (as measured by the data logger) and ‘diver’ as factors.

Analyses of distance-based catch-per-unit-of-effort (CPUD)

An ANOVA was performed with CPUD as the dependent variable and ‘diver’ (A, B or C) as a factor to test for differences in CPUD between divers.

Analyses of area-based catch-per-unit-of-effort (CPUA)

A two-way ANOVA on area-based catch-rates was performed with ‘method’ (the three different area-based indices of abundance: CPUA_{mcp} based on a Minimum Convex Polygon, CPUA_{buf} based on a buffered vessel track and CPUA_{kde} the 95% density contour from a Kernel Density Estimate) and ‘diver’ as factors, including interactions between method and diver.

To stabilise residual deviance when needed, some of the response variables were transformed (log-transformed, or square-root transformed). Results of statistical tests are presented on untransformed data, when transformations did not affect the significance of the results (see Appendix 4). Box-Cox tests were performed using the R function of the same name (‘boxcox’).

3.3 Results

Each whole day of fishing was treated independently in these analyses. This forced level of aggregation was caused by the scale of catch-reporting and is in contrast to the analyses in Chapter 4 where each fishing event was treated independently.

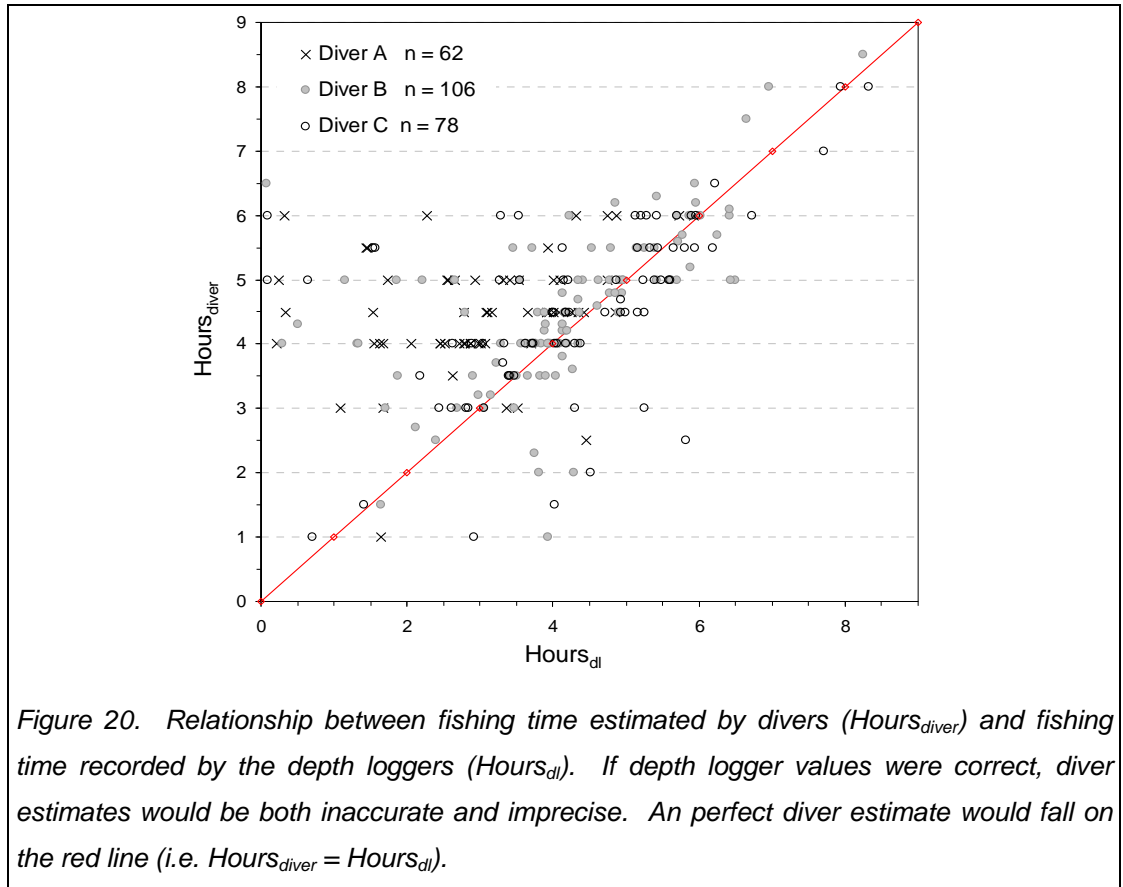
3.3.1 Measuring time: disparities between logger recorded and diver reported dive times?

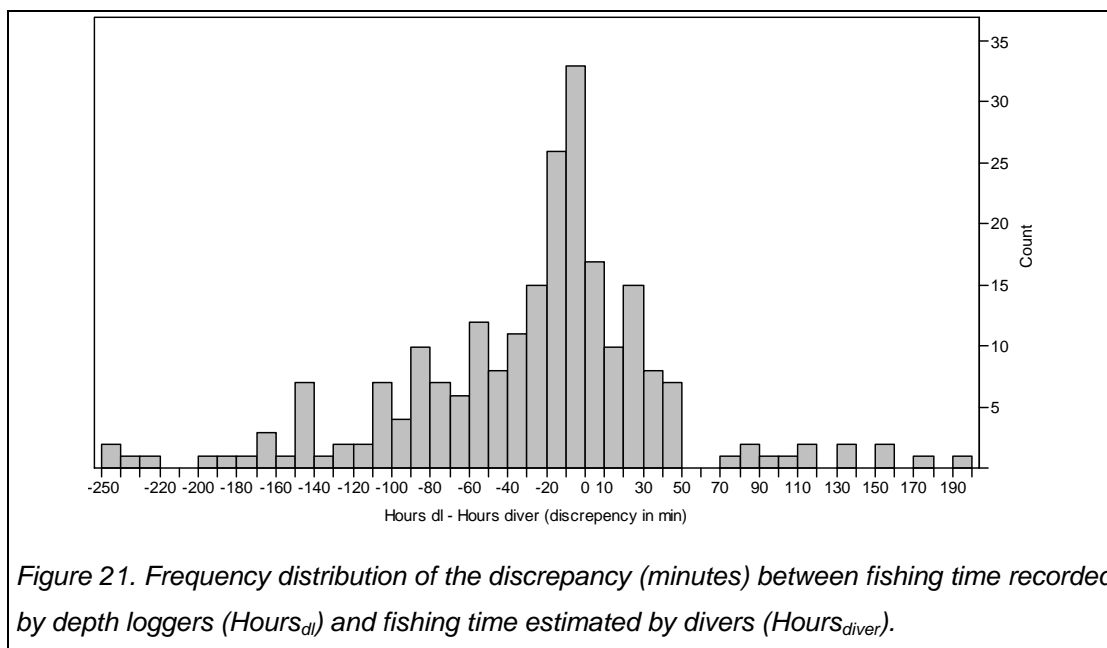
Duration of fishing activity

Fishers frequently reported their estimates of total fishing time imprecisely, in whole hour and half hour blocks. Occasionally one diver reported fishing time to the nearest 15 minutes (Figure 20).

Diver estimates of daily fishing effort duration were not always close to time recorded by loggers (Figure 21). The mean difference was an overestimate of 5.3% of fishing time reported by a diver relative to the time measured by the data

logger. This difference was due to a combination of diver error and depth logger error. Diver 'overestimates' are shown in Figure 21 as negative discrepancies. Visual inspection of the data in Figure 20 and Figure 21 indicates that Diver A almost consistently reported an estimated fishing time higher than that measured by the logger. Across all divers, an 'overestimate' of fishing time was more frequent (72% of all fishing days) than an 'underestimate'.





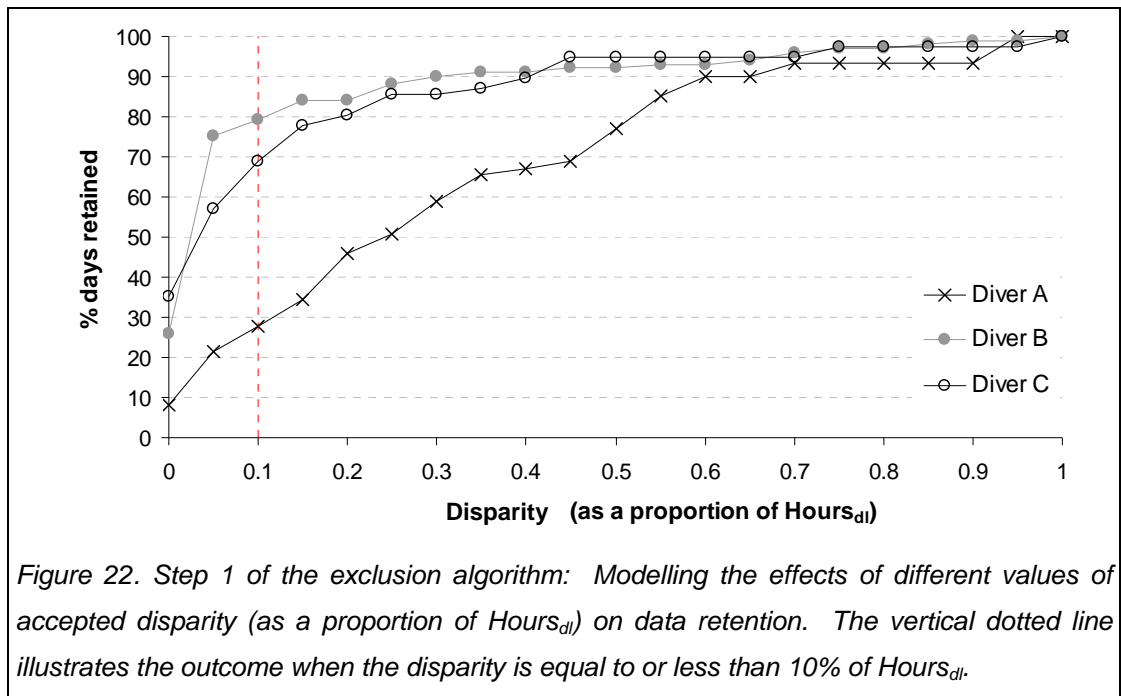
However, during preliminary exploration of time data pooled across all divers (226 observations; see Figures 20 and 21), investigation of outliers, i.e., extreme values of discrepancy between $CPUE_{dl}$ and $CPUE_{diver}$ revealed malfunctions in the equipment used to collect fishing time data, in addition to the imprecision in fishing time that was reported by divers. Note that the presence of some extreme differences between the two indices reflect either inaccurate depth logger data due to equipment malfunction, or may also have occurred when divers did not wear the logger for all dives during a fishing day. Raw data were filtered to remove these erroneous data records. The next section of this chapter describes the filtering process of the raw data.

3.3.2 Selecting Days for Spatial Catch Rate Analyses

Step 1 of Data Exclusion Algorithm

Across all divers, the disparity between $Hours_{dl}$ and $Hours_{GPS}$ ranged between 0 and 445 minutes in a day. At 0 minutes no spatial data were missing from the day's effort dataset. At 445 minutes almost 7.5 hours of fishing had been recorded by that dive logger, for which no spatial data were collected. The distribution of disparity between $Hours_{dl}$ and $Hours_{GPS}$ was different for each of Diver A, B and C but for all divers this disparity was most often <10 minutes: 75% of days with depth logger data for Diver B ($n = 106$), 53% for Diver C ($n = 78$) and 28% for Diver A ($n = 65$).

In Figure 22, x is plotted as an accepted disparity between Hours_{dl} and $\text{Hours}_{\text{GPS}}$. Up to 10% disparity in dive duration between the two data sources ($x = 0.1$) was considered acceptable (i.e. 10% of depth logger recorded fishing activity had no matching GPS data). Retention in step 1 was 32% for Diver A, 80% for Diver B and 69% for Diver C. This trade-off between data quantity and quality was necessitated by problems encountered in data collection (see Chapter 2) and balanced the exclusion of days with lots of GPS data missing with a desire to retain a dataset of sufficient size for analysis.



Step 2 of Data Exclusion Algorithm

In Figure 23 the accepted error in diver estimate (y) is modelled as the 'error' in diver estimates of dive duration ($\text{Hours}_{\text{diver}}$) compared to dive duration measured by depth logger (Hours_{dl}). This step excluded days when a diver estimate of dive duration was much greater than the measured duration, indicating that some diving may have gone unlogged by both the GPS and depth/temperature data loggers. y was limited to $\leq 30\%$. At the $(\text{Hours}_{\text{dl}} + 30\%)$ exclusion rate, retention in step 2 was 62.5% for Diver A, 97.5% for Diver B and 97.6% for Diver C (see Table 5 for details). The percentage of days retained in the dataset reached a plateau or near-plateau for divers A and B when a +30% error acceptance rate was applied (vertical dotted line). Diver C was an exception (cf Figure 24).

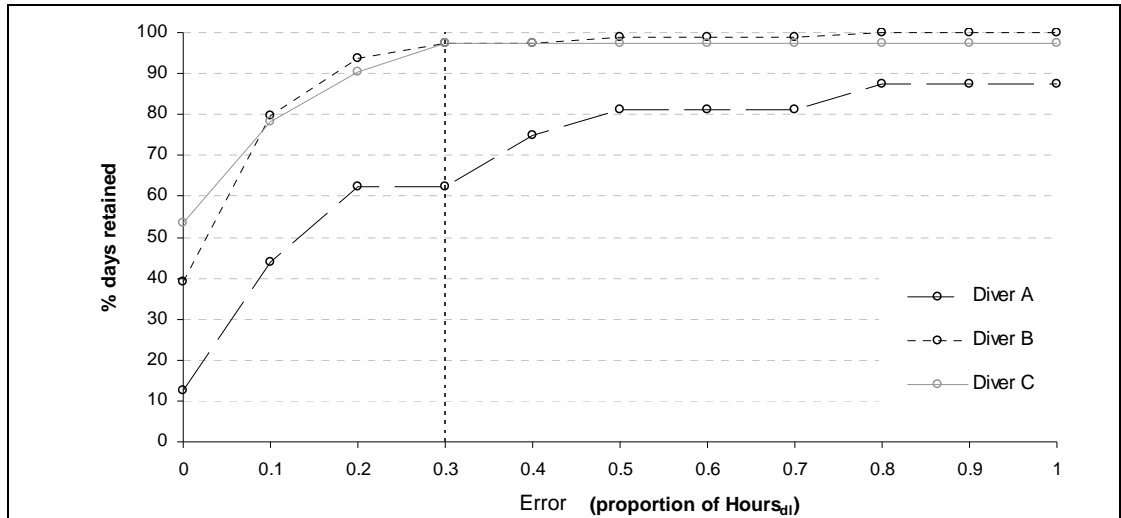


Figure 23. Step 2 of the exclusion algorithm: the percentage of days of data retained for CPUE analysis as a function of discrepancies in dive duration.

Days of Data available for Spatial Analysis after Filtering

Following the steps of the data exclusion algorithm led to the exclusion of many days of data from the dataset available for calculating CPUE. Of the original dataset, only 21% of days for Diver A were retained, 78% for Diver B and 68% for Diver C (Table 5 and Figure 24).

Table 5. Summary of data exclusions for each diver.

		Diver A	Diver B	Diver C
Days with matching GPS and depth logger records		62	106	78
STEP 1	Hours _{dli} > (Hours _{GPS} x 1.1)			
	exclude	42	21	24
	keep	20	85	54
STEP 2	Hours _{dli} > (Hours _{diver} x 1.3)			
	exclude	7	2	1
	keep	13	83	53
Days remaining as % of original		20.97	78.30	67.95

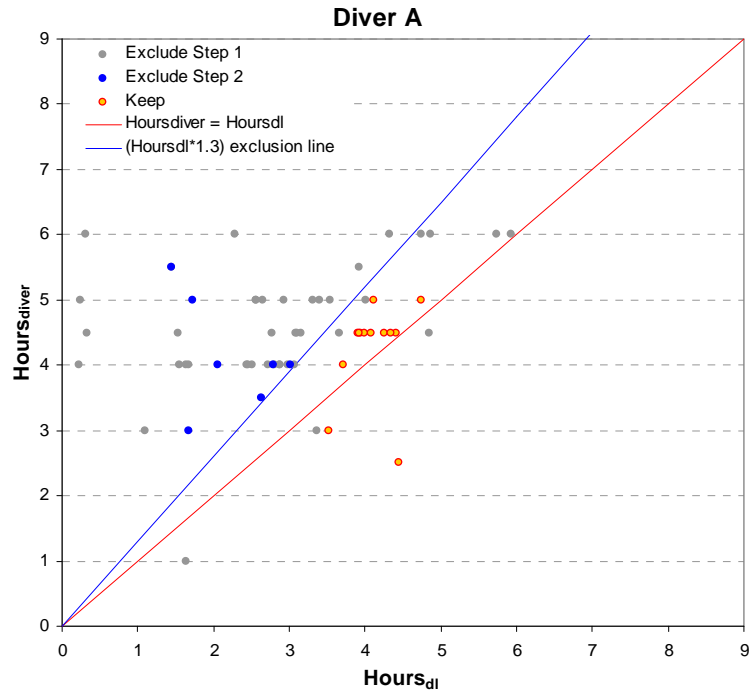


Figure 24a. Days of data kept following the data exclusion algorithm (shown in orange) for Diver A. Points falling above the blue line were excluded at a +30% exclusion rate in step 2 (cf Figure 23). An accurate diver estimate (Hours_{diver} equal Hours_{dl}) falls on the red line when the depth logger captured all dive data (i.e. was deployed on all dives for a day).

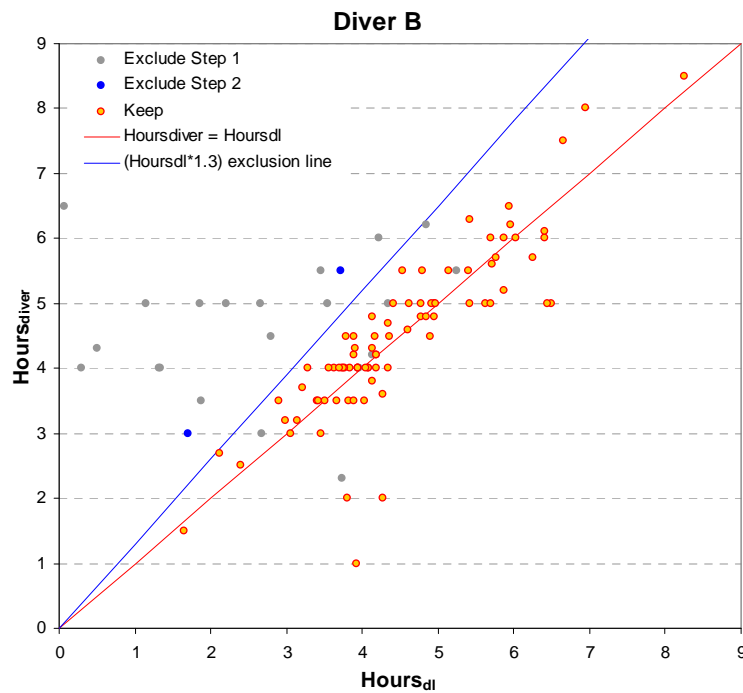


Figure 24b. Days of data kept following the data exclusion algorithm (shown in orange) for Diver B.

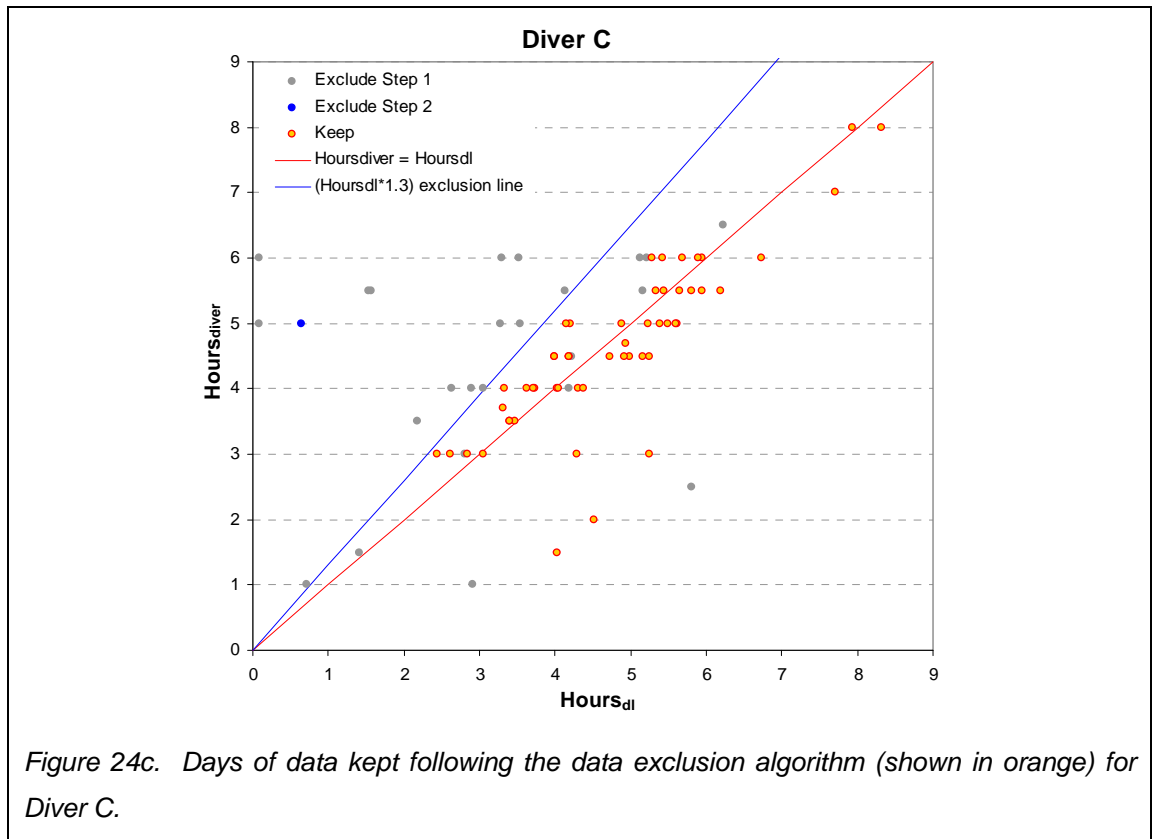


Figure 24c. Days of data kept following the data exclusion algorithm (shown in orange) for Diver C.

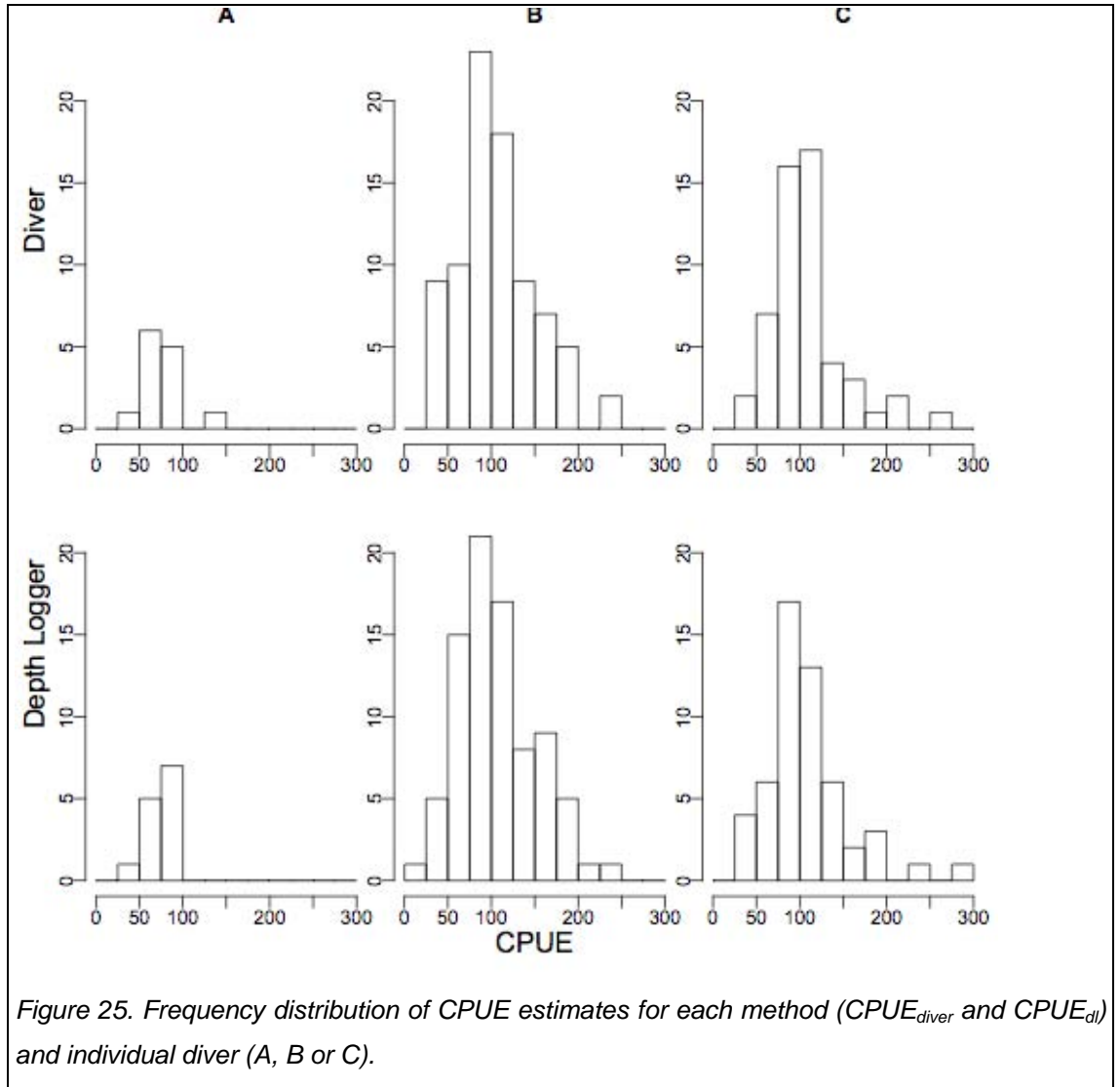
All results presented hereafter are derived from analyses performed on the filtered data set.

Effect of error in time reporting on daily CPUE

Using the filtered data, the mean absolute discrepancy between Hours_{diver} and Hours_{dl} was significantly different to 0 ($F_{1,146}=121.47$ - P inferior to 0.0001) and consistent across all divers ($F_{2,146}=0.60$; P = 0.5489).

Both inaccuracy and imprecision in diver's effort estimates are reflected in the discrepancies between CPUE_{diver} and CPUE_{dl} (Figure 25). Note that CPUE data, as plotted in Figure 25, also reflects any errors in catch data, but misreporting of catch data is outside the scope of this study.

The ANOVA reveals that individual divers (A, B or C) have a significant effect on mean CPUE values ($F_{2,292}=6.7028$; P=0.001425), while there was no difference between the two CPUE methods ($F_{1,292}= 0.0338$; P= 0.854) and nor is there an interaction between diver and method ($F_{2,292}=0.0401$; P=0.9607).



3.3.3 Measuring Distance: Creating a path of vessel movement

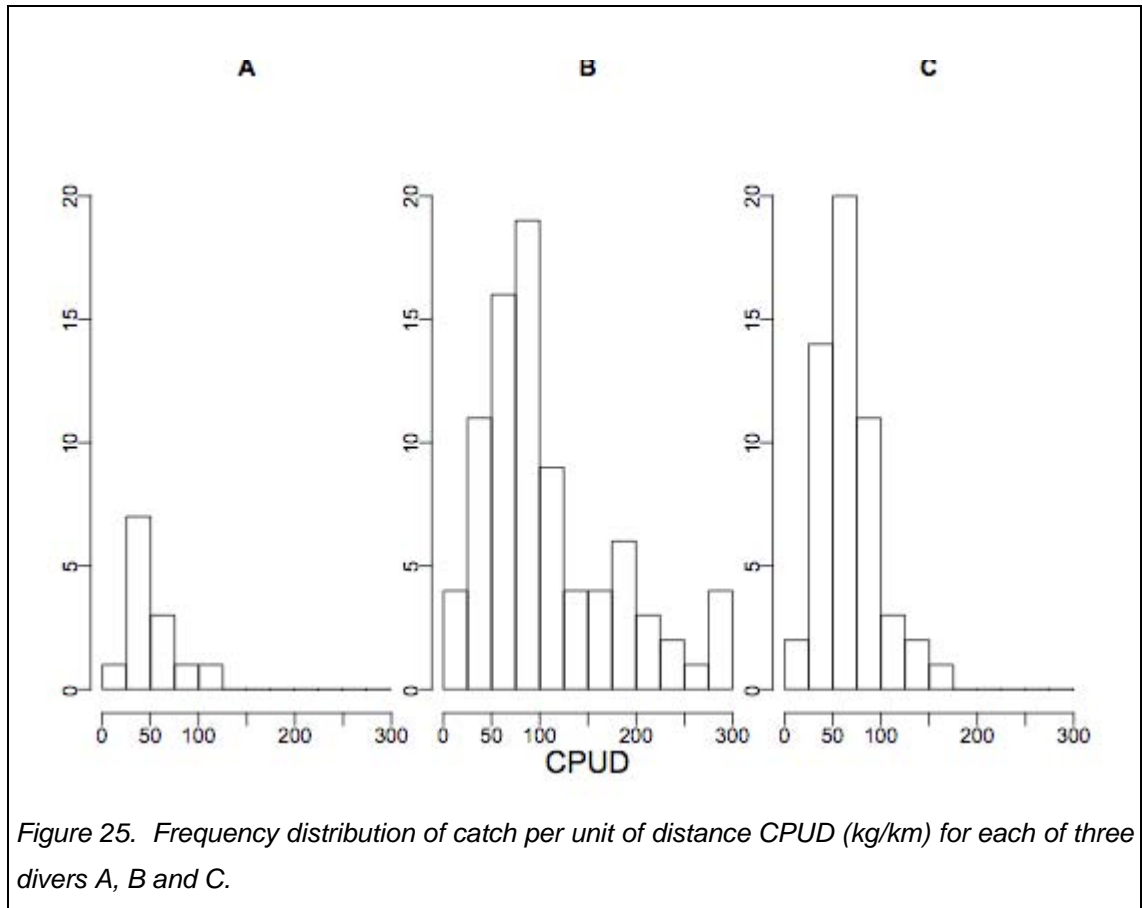
Across all divers, daily summed path lengths ranged from 1.2 km to 15.4 km ($n = 147$). For diver A, the mean daily path length was 6.1 km, for Diver B it was 5.2 km and for Diver C it was 7.9 km (see Table 6 for a summary).

Table 6. The sum of path lengths (m) for each. One outlier was excluded from datasets for each of Diver B and Diver C.

	Diver A	Diver B	Diver C
Mean	6061.65	5191.33	7947.67
Std Dev	1990.49	2251.99	2938.94
Std Err Mean	552.06	248.69	407.56
upper 95% Mean	7264.50	5686.15	8765.87
lower 95% Mean	4858.81	4696.52	7129.46

Daily Catch per Unit of Distance

For each day of catch in the filtered dataset a value of catch per unit of distance (CPUD) was calculated (Figure 25). Results from the analysis of variance suggest that 'diver' has a significant effect on CPUD estimates ($F_{2,143}=15.77$; $P=6e-07$).

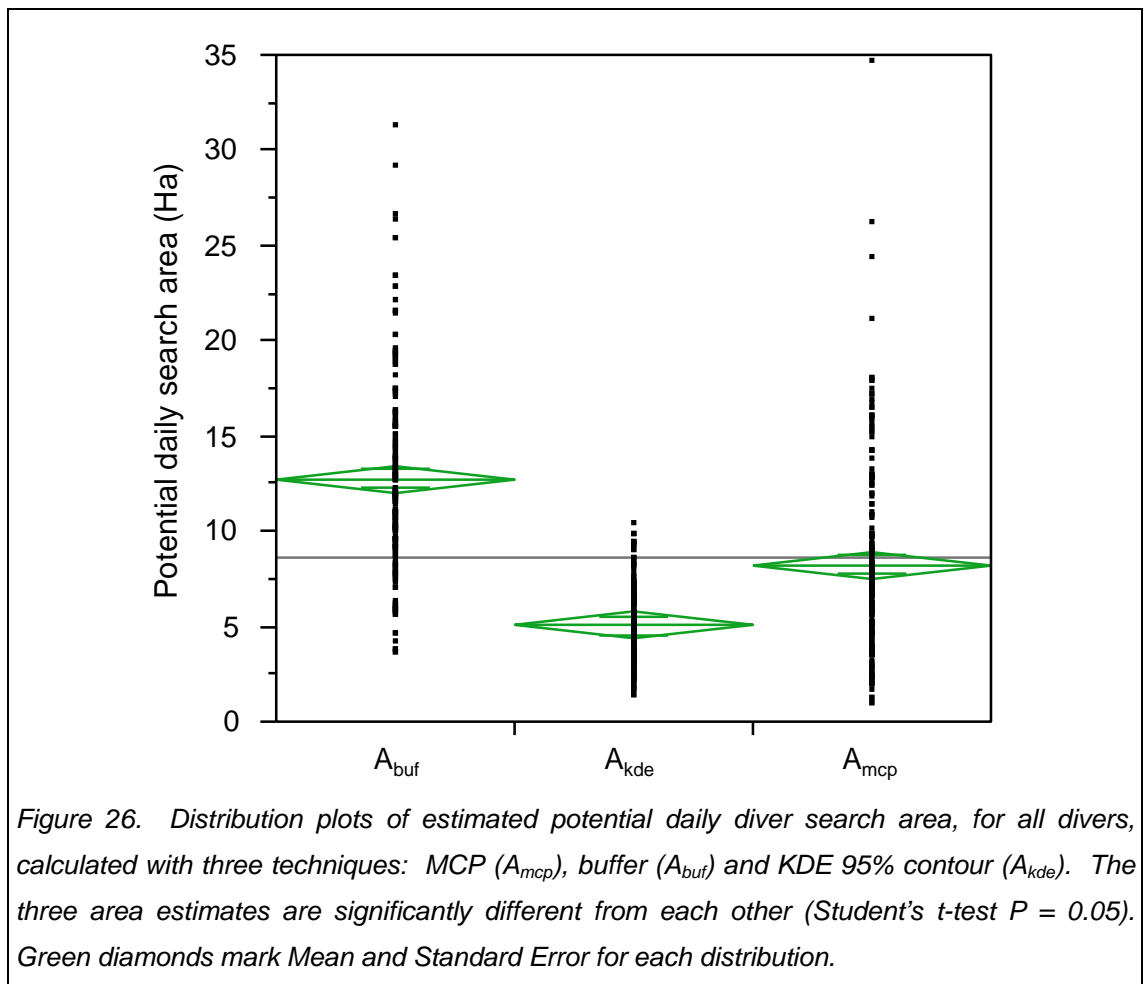


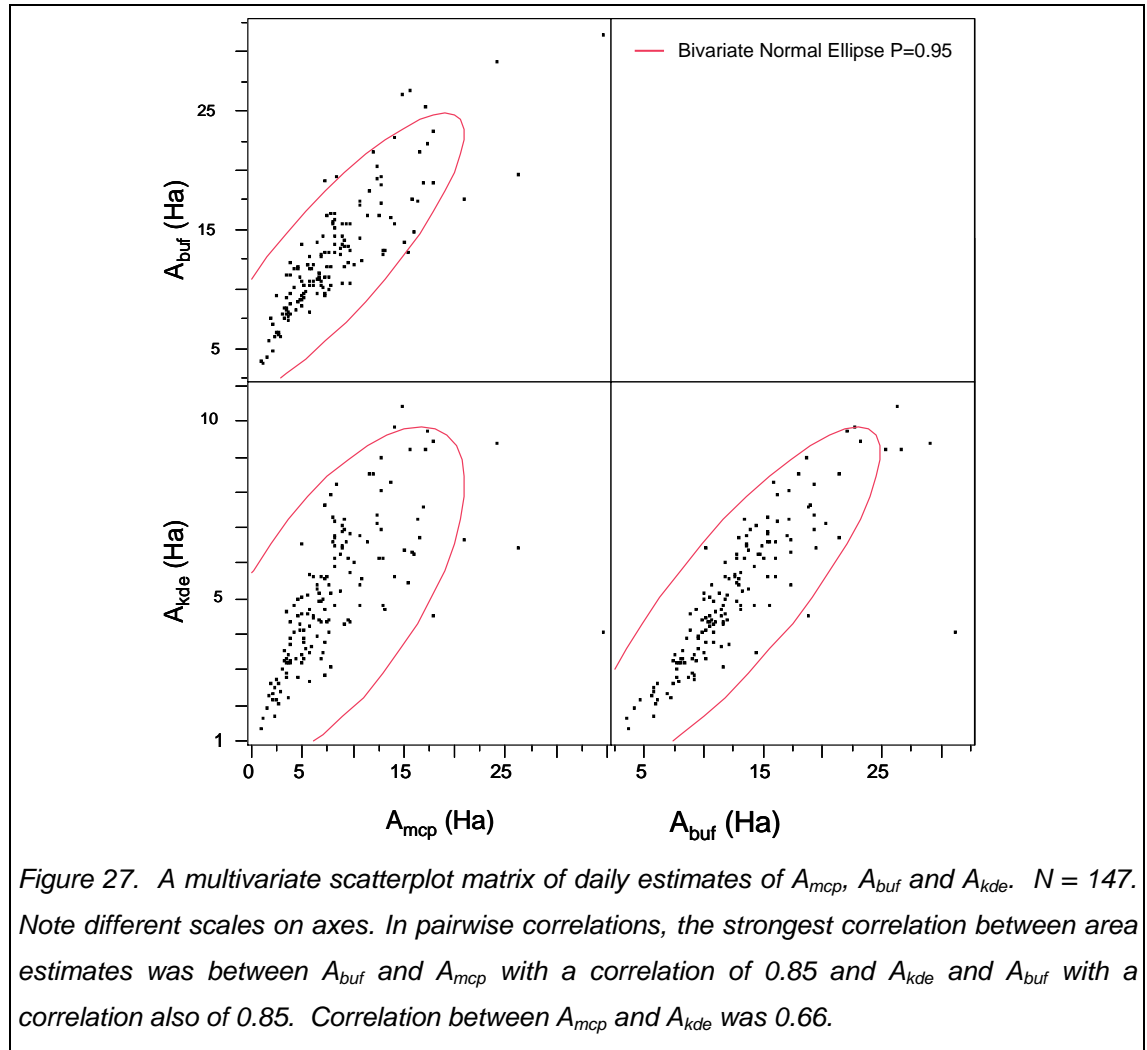
Comparison of CPUD for Diver C and Diver B reveals very different foraging strategies between the two fishers: Diver B intensively harvests individuals along the distance covered relative to Diver C, who appears to be covering longer distances to achieve a similar $CPUE_{dl}$.

The small sample size here means that future investigations would be required across a wider proportion of the fishery to further explore the use of the relationship between CPUD and time-based CPUE to characterise different harvesting strategies.

3.3.4 Measuring Area: An index of diver ‘search’ area

Three estimates of available search area were generated for every fishing event: a Minimum Convex Polygon (A_{mcp}), a buffered vessel track (A_{buf}) and the 95% density contour from a Kernel Density Estimate (A_{kde}). For each diver, area estimates of single fishing events were summed across a day to calculate a potential daily search area. There were some significant differences in CPUA indices between divers (ANOVA: $F_{2,438} = 10.9549$; $P = 2.278 \times 10^{-5}$) and between methods of estimating potential search area (ANOVA: $F_{2,438} = 64.9128$; $P < 2.2 \times 10^{-16}$). See Table 11 in Appendix 4 for posthoc comparisons. A_{buf} estimates were approximately twice the area of A_{kde} estimates. A_{kde} was almost consistently the lowest estimate and A_{buf} the highest (Figure 26).





A_{kde} as a measure of diver search area

For the following comparison of CPUA with traditional time-based CPUE, A_{kde} was chosen as the estimate of search area available to a diver while fishing. Comparison between CPUA indices and traditional CPUE measures were restricted to the A_{kde} area index for clarity. Results presented here for the A_{kde} spatial index may be valid for other spatial indices, but these would have to be tested further. Note again that this measure of area relies on spatial information about the fishing behaviour of combined diver and vessel, and does not correspond to the actual amount of area searched by a diver. No data were available on exact diver location or on the spatial relationship between vessel movement and diver search patterns. A_{kde} for each day of fishing for Divers A, B and C ranged in value from 1.3 to 10.3 ha ($n = 147$). Mean daily A_{kde} for Diver A was 4.64 ha, Diver B was 4.46 ha and Diver C was 6.10 ha (See Figure 28 for frequency distributions and Table 7 for descriptive statistics).

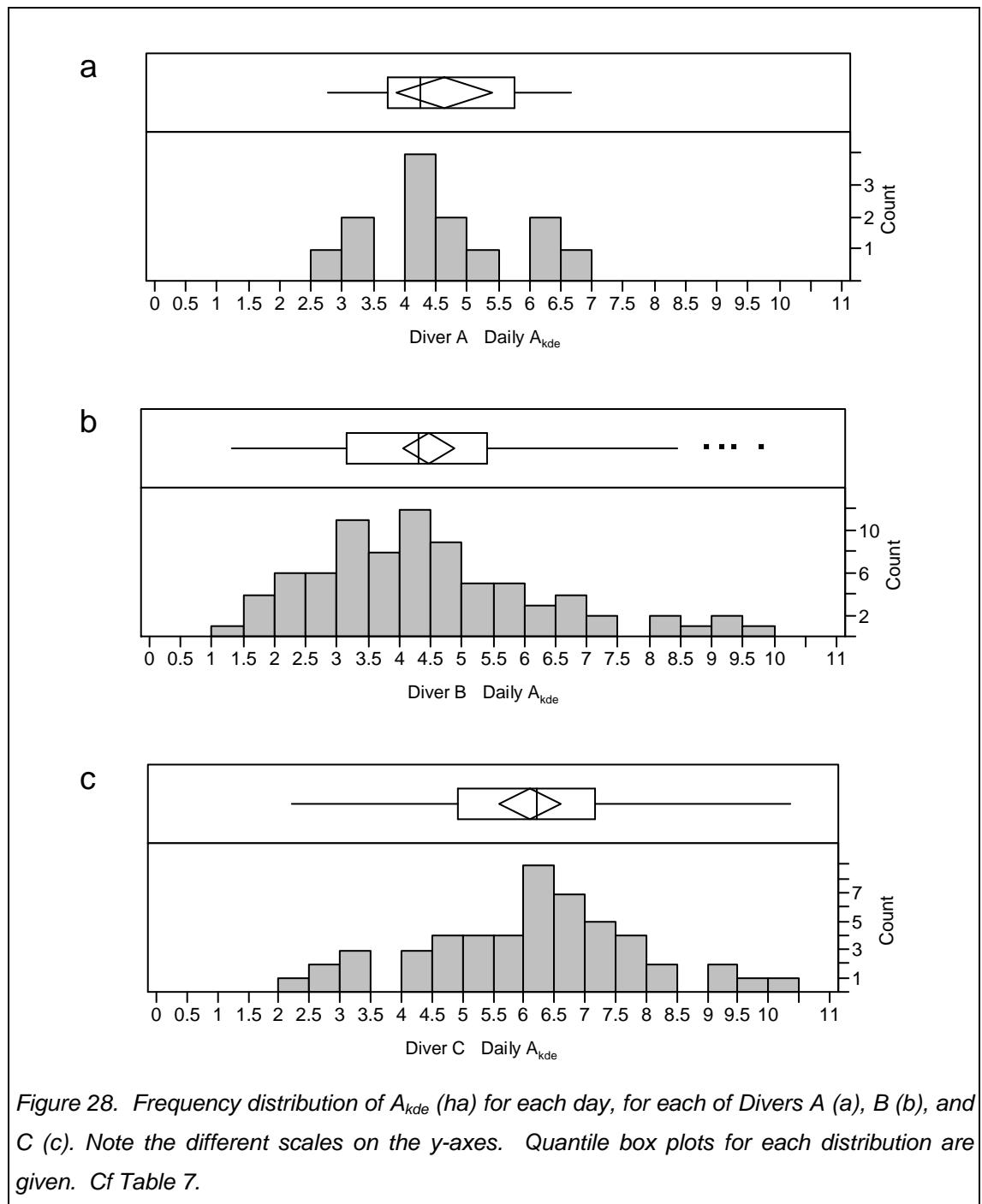


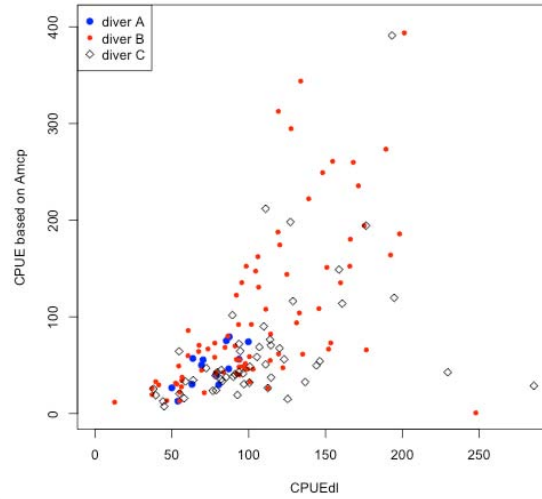
Table 7. Descriptive statistics for the frequency distributions of A_{kde} (ha) for Divers A, B and C. Cf. Figure 28.

	Diver A	Diver B	Diver C
Mean	4.640	4.463	6.104
Std Dev	1.257	1.888	1.798
Std Err Mean	0.349	0.208	0.249
upper 95% Mean	5.400	4.878	6.604
lower 95% Mean	3.881	4.048	5.603
N	13	82	52

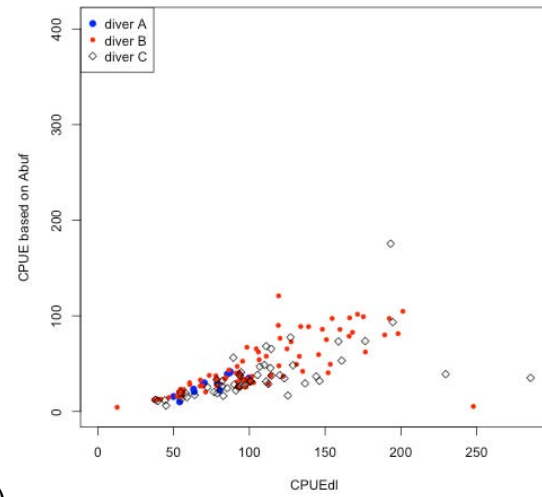
Daily Catch Per Unit of Area (CPUA)

For each diver and each day of fishing, the catch rate per unit of area (CPUA) was calculated in kg/Ha. There were some significant differences in CPUA values between methods of estimating potential search area (ANOVA: $F_{2,438} = 14.570$; $P < 7.5e-7$). The effect of individual divers was not significant ($F_{2,438} = 1.171$; $P = 0.311$). The three area-based CPUE estimate perform differently to each other.

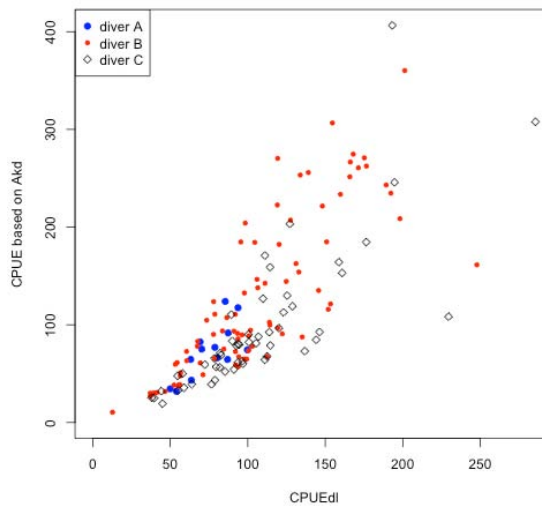
A visual inspection of the relationships between catch per unit of area (CPUA) using the three different estimates of searched area against traditional time-based CPUE ($CPUE_{dl}$) was performed for each fishing day and per diver (Figure 30). These plots illustrate the divergence in the different area-based indices of CPUE. Similarly to the relationship between time-based CPUE and distance-based CPUD (cf. previous sections), it would be worthwhile investigating the relationship between CPUA and CPUE as a measure to characterise individual fishing behaviour. In terms of fine-scale monitoring of fishing activity, it would be particularly relevant to test whether some ‘types’ of harvesting behaviours defined using these indices consistently emerge across divers of the Tasmanian abalone fishery. The small sample size did not allow for such investigation in this study.



(a)



(b)



(c)

Figure 29. Catch per unit of area ($\text{kg} \cdot \text{ha}^{-1}$) derived from A_{mcp} (a), A_{buf} (b) and A_{kde} (c) plotted against CPUE ($\text{kg} \cdot \text{hr}^{-1}$) for each of three divers A (solid blue dots), B (solid red dots) and C (black diamonds). Similar x and y scales are used to facilitate visual comparison.

3.4 Case Study: using spatial indices to standardise catch rates

This case study focuses on the diver identified as “Diver A”. I have previously discussed the differences between the alternative measures developed to estimate catch rate across all divers. Here, I focus on demonstrating the different standardised spatial indices that I have developed in Chapter 3, using 13 fishing days of data recorded by Diver A.

To rank the quality of the different abundance indices would require specific knowledge about actual abundance of abalone in the study area. Instead, this section aims to illustrate the effects of the different standardisations of fishing effort on catch rate estimates. Standardisation could reduce and would ideally eliminate the effects on catch rate of different fishing gear, fisher experience and fishing habitat (Haddon 2001). Because divers differ in their performance, as measured by CPUE, CPUD and CPUA, such catch rate measures should be standardised when used as an index of abundance. Catch rate improves as a measure of abundance after standardisation. In the Tasmanian abalone fishery, diver catch rate standardisation is performed using a combination of factors including diver, season (month) and location (statistical block) (Tarbath *et al.* 2007). A measure of effort distribution could improve standardisation of catch rate when it is used for assessment. Currently, it is possible for CPUE to remain constant while the spatial distribution of effort changes. A precise measure of effort distribution in space and time such as area or distance covered while fishing should improve the spatial distinction of effort.

This case study focuses on the fishing effort of one diver working the Actaeon Reef in southeast Tasmania between January 2006 and April 2007. Thirty-one dives over 13 days of fishing provided data for 8 catch rate estimates, after 5 days were excluded from analysis during data filtering (Figure 30 and Table 8).

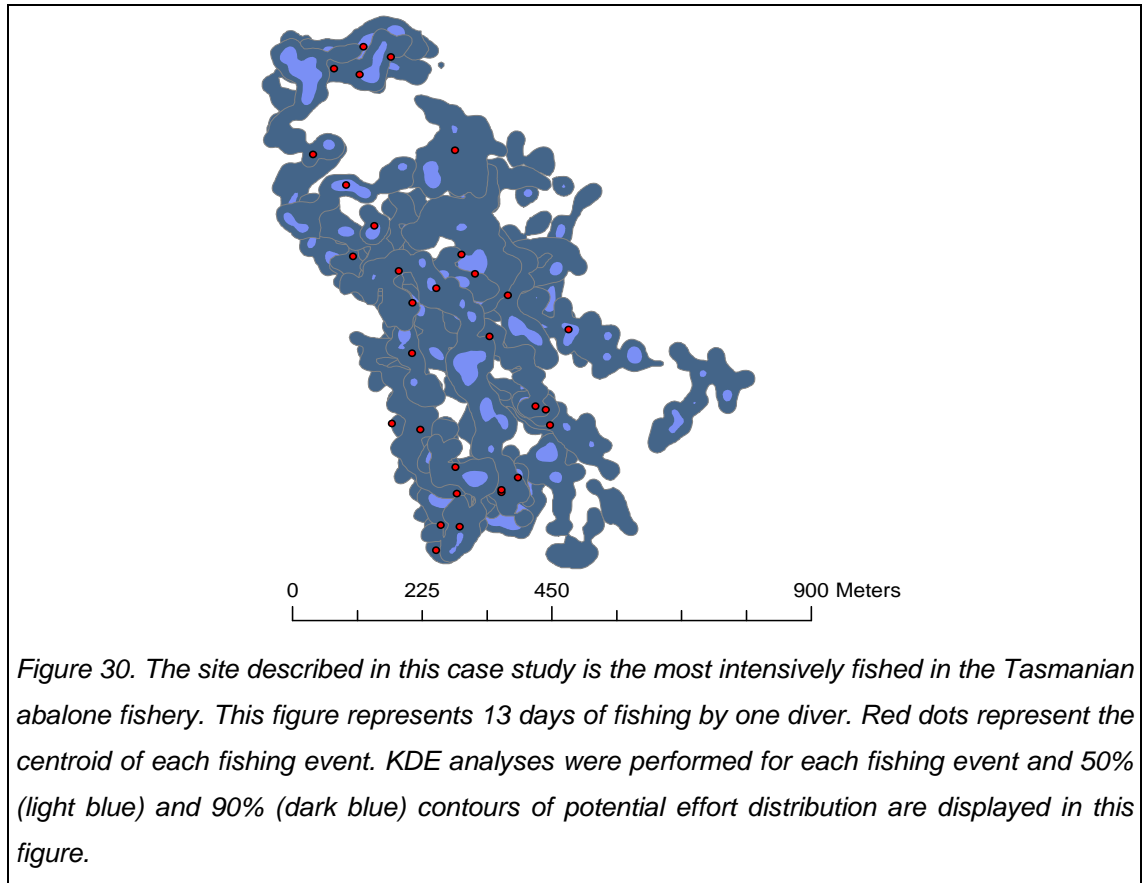


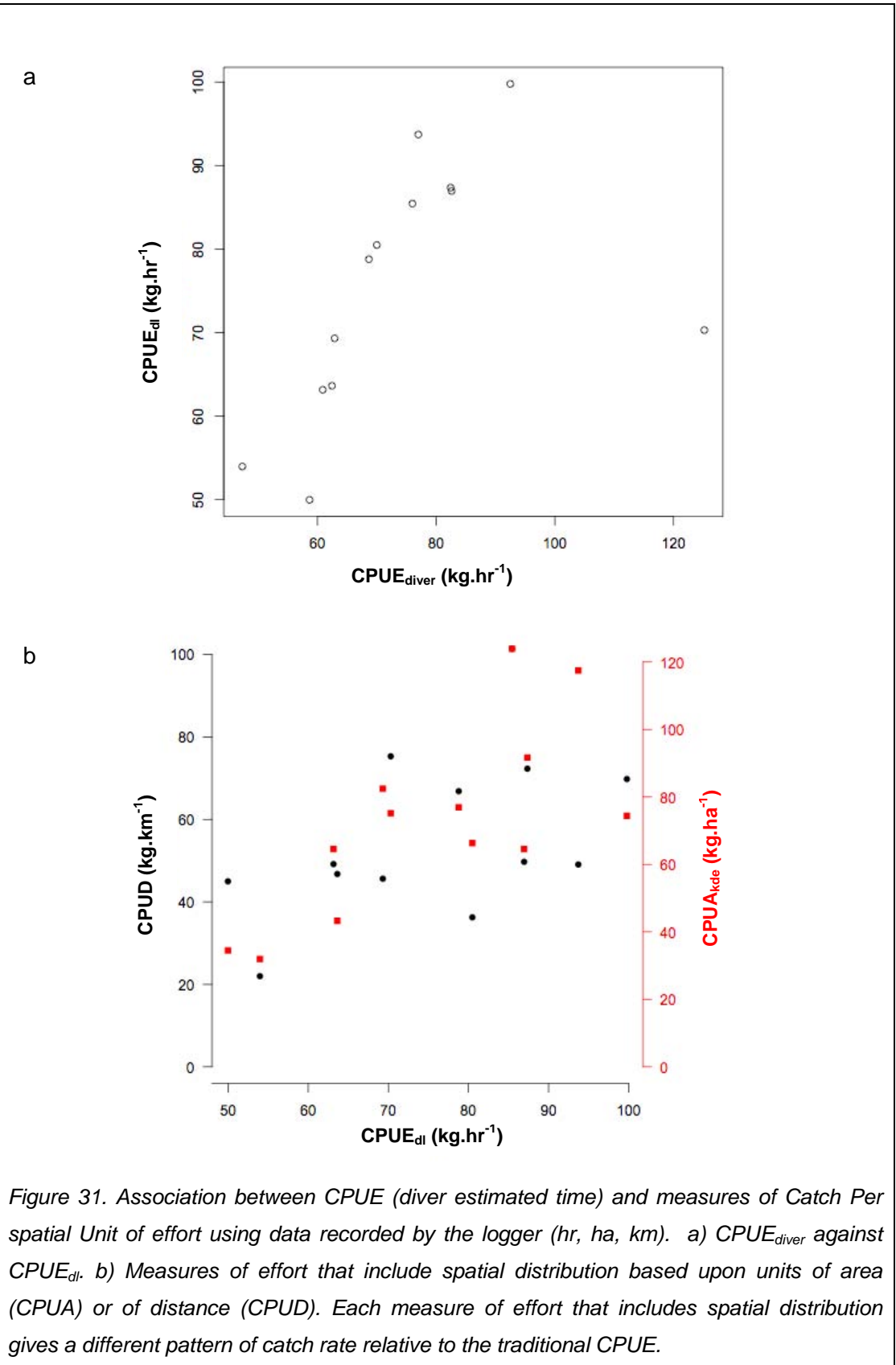
Table 8. Fishing activity of one diver working the Acteon Reef between January 2006 and April 2007

Date	Number of Events	CPUE Data available?
25-Jan-06	5	Yes
03-Feb-06	4	Yes
16-Feb-06	2	-
30-Mar-06	5	Yes
13-Apr-06	2	-
17-Apr-06	3	Yes
18-Apr-06	4	Yes
05-Jul-06	1	-
19-Jul-06	4	Yes
20-Jul-06	4	-
26-Sep-06	3	Yes
16-Oct-06	1	-
15-Apr-07	4	Yes

3.4.1 Exploring the benefits of spatial effort data

Diver underestimates of dive time resulted in overestimates of CPUE (Figure 31). Catch rates were artificially enhanced by this diver's error in estimating dive time.

Using the area of the 95% KDE contour rather than distance as a spatial measure appears to eliminate some movement of the vessel that is not associated with diver movement (Figure 31).



By looking at the relationship between catch, time, and area covered while fishing, spatial measures of effort can be incorporated into interpretations of catch rate. Fishing search rate can be calculated as the estimated amount of 'area fished' by a diver (derived from GPS data) in a unit of time to give a search rate in hectares per hour (CPUA) (see section 3.2.4 'Catch Per Unit Area' for methods). For this case study, Search Rate (Ha/hr) was plotted against catch rate (CPUE in Kg/Hr) (Figure 32).

Including spatial data in measures of fishing effort identifies two separate activities that involve time; primarily searching for abalone and primarily handling abalone. In Figure 32 two patterns of behaviour identify two types of effort distribution. When traditional catch rates are high (above 90 Kg/hr) then the diver can be considered to be exhibiting "fishing" behaviour. CPUE may be limited by 'handling time' and not 'search time'. When traditional catch rates are low (below 90 Kg/hr) then more searching behaviour is seen. There is a strong negative correlation between search rate (in Ha/hr) and catch rate. When the diver is swimming and covering area, they are not catching a lot of abalone.

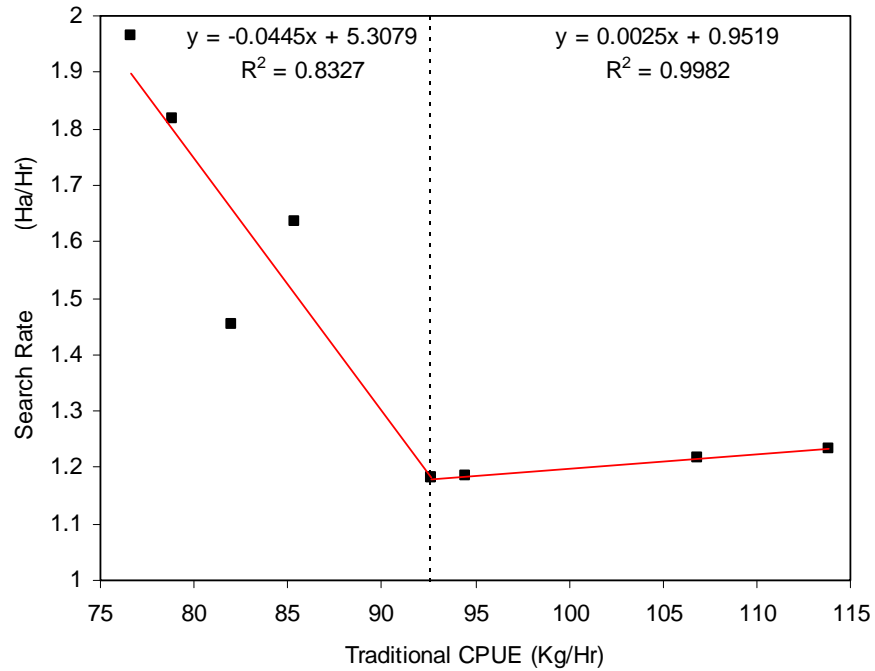


Figure 32. Eight data points derived from the 13 days of fishing activity illustrated in the map in Figure 30. There is a negative correlation between search rate and catch rate up to a threshold catch rate (Kg/Hr). Above the threshold, search rate is almost constant despite increasing catch rates.

3.4.2 Conclusions

Data loggers enable researchers to collect large amounts of data, however, rigorous attention to collecting good quality data is important as poor quality data are necessarily discarded from datasets. The site described here is the most intensely fished in the Tasmanian abalone fishery. Plotting search rate (ha/hr) against CPUE (kg/hr) for this site has identified a threshold at which fishing behaviour appears to change from 'searching' (swimming and covering area) to 'fishing' (little area is covered and catch rate is high). It could be very valuable to be able to easily categorise different patterns of diver distribution of effort between fishing (handling) and searching activities. If a change in fishing behaviour can consistently be identified by the relationship of CPUE to CPUE then it might be used to standardise for effort during data filtering.

3.5 Discussion

3.5.1 Efficacy of electronic methods for effort capture

Improving measurements of effort

Using depth loggers to record fishing duration can potentially improve CPUE estimates by providing a convenient means of accurately measuring the duration of fishing activity for each day of fishing. Divers regularly round their estimates of fishing time spent to the nearest half hour, with the estimates reported to DPIW being approximate and often inaccurate. Divers do not necessarily refer to a dive computer when recording catch and effort details at the end of a day's fishing, which may contribute to the inaccuracy. Historically, a reported 'best guess' estimate of time spent fishing has been considered sufficient by fishery managers and researchers (Tasmanian Abalone Council Ltd 2002). Nevertheless, this study suggests a significant absolute difference between time reported by divers and measured by depth loggers. On average in this study, divers appeared to overestimate the amount of time they spent fishing, most frequently by 0-10 minutes (see Figure 21), but the sign of the error (i.e., over- or under-estimate) significantly varied between individual divers. Importantly, failure to wear depth loggers while diving was flagged as a cause of apparent overestimate of dive time, (Section 3.5.1).

Effects of improved effort measurement on CPUE

Errors in time estimate did not significantly affect CPUE estimates for the three divers who participated in this study. However, further investigations using more reliable time data collection across a wider proportion of the Tasmanian abalone fishery would be essential to confirm these results. Consistent errors in dive time estimation by just a few divers in the fishery may be enough to artificially inflate or deflate catch rates calculated from diver estimated fishing durations. This would affect fishery-wide catch rates as they are currently calculated. Note that inaccurate reporting of catch data by divers (see Section 3.3.1 'Daily CPUE') can be another possible source of error in calculation of CPUE, which is outside the scope of this study.

As mean values of CPUE with both methods are significantly different for individual divers, these results suggest that accounting for fine-scale fishing effort can be

worthwhile to better account for discrepancies in individual divers' fishing efficiency: among the 3 divers involved and across both time-based methods, Diver C showed the highest mean CPUE, and Diver A the lowest (Figure 25). Moreover, results suggest significant differences in fishing efficiency (CPUE) between the three individual divers. Despite the small sample size of this study, these consistent differences between individual divers illustrate the value of fine-scale monitoring of fishing effort. These results do require further investigation, as i) the sample size of this study is small and may not be representative of the whole abalone fishery, and ii) reliability of fishing time data as recorded by data loggers is questionable, as raw data had to be filtered to remove extreme discrepancies between the two time measures. Assuming a similar diversity amongst other divers with respect to fishing efficiency, fine-scale monitoring of fishing effort can address these discrepancies between divers and complement current coarse-scale fishery management.

Problems with data collection and use of equipment

The data used in this study were collected during the initial trials of methods used to collect fine scale spatial data from the Tasmanian abalone fishery. The problems identified in this study will assist with improving data collection processes using these methods.

The data-filtering algorithm applied to the dataset prior to generating spatial effort measures was cumbersome, but was required because the spatial (GIS) dataset was incomplete. The filtering process had to find a balance between excluding days that had data missing, and retaining enough days so that statistical analyses were possible. The dataset incorporated many days of fishing for which some spatial data were missing, due to faulty GPS loggers, battery connections or incorrect use of the equipment by divers. In Chapter 2 this was flagged as an issue in a strategic data collection program. Data were filtered to exclude days that had GPS records missing and days on which divers did not wear depth loggers.

Ideally, all days with any spatial data missing would be excluded from the dataset. With a reliable power supply GPS loggers could always be left on and very little spatial data would be lost. If this can be achieved, then the rules for accepting days of data at step 1 could be tightened. Days with more than 5% of GPS data missing might be excluded rather than days with more than 10% missing. If divers were known to be wearing depth loggers for all fishing activity then step 2 of the filtering

algorithm could be dropped. Depth logger measured dive duration could supplement or replace diver estimates of duration in CPUE calculations.

Through the data filtering process 40% of days of fishing data were excluded. A majority of these days were from one diver (A), however, even for divers B and C combined 25% of days of fishing were excluded. In the context of fisheries management, this would not be an acceptable loss of data. Clearly, data collection techniques need to be improved to capture all spatial (GPS) and fishing (depth logger) data for each day of fishing. Since the goal of this study was to test the feasibility of applying techniques, rather than attempt to use all available data to assess the fishery, this loss of data is acceptable. If data are to be used to calculate CPUE estimates for fishery management purposes, future data collection programs will need to:

- Ensure a reliable power supply for GPS loggers
- If possible, encourage divers to leave depth loggers attached to dive gear at all times
- Ensure that data loggers have sufficient capacity to store all data collected
- Follow a regular program of data retrieval from loggers

Following these suggestions will guard against loss of data and reduce the need for the data filtering algorithms applied here.

3.5.2 Measuring distance from a path of vessel movement

The length of path travelled by a vessel each day will partly be determined by the swimming pattern of a diver underwater, however, the way that the deckhand manages the boat will also affect the length of vessel track. Thus, the cause of differences in length of vessel path cannot be attributed solely to diver movement and 'fishing behaviour' is results from a combination of deckhand and diver behaviours. In future research on fine-scale spatial monitoring of abalone fishers, efforts should go towards better defining this poorly known relationship between vessel and diver movements.

The length of path travelled by a vessel each day is also dependent on the temporal resolution of data sampling (Turchin 1998, Ryan *et al.* 2004, Deng *et al.* 2005)⁷. A more frequent sampling rate will generate a longer track as smaller movements are captured. When sampling frequency is irregular, the rate of

⁷ see Chapter 2 for more detail on data sampling methods

movement rather than distance has been used to standardise variation (Turchin 1998). All data collected for this study were sampled at a 10-second time interval so path length is a viable measure of displacement for equal time intervals. It will be essential to determine the most appropriate time resolution for monitoring to ensure the collection of high quality data about vessel movement in the future.

Mean vessel path length significantly varied between divers. For instance, mean path length for Diver C was significantly longer than for Divers A and B. This can be interpreted in several ways:

- Diver C dived for longer each day, covering more distance;
- Diver C fished in locations where abalone were sparse and he/she needed to swim further to take a day's catch;
- Diver C's deckhand managed the boat differently than the deckhands for A and B, laying down more 'path' independently of diver movement, e.g. by zigzagging over the diver's path.

Discrepancies in distance covered by divers in combination with additional information about catch-rates and estimates of searched area can help to characterise different foraging behaviour (cf. following sections).

3.5.3 Use of GIS tools to calculate spatial structure parameters for fishing events in dive based fisheries

Measuring Distance

Data were sub-sampled at several different time intervals and the sampling interval chosen that provided movement parameters which most accurately reflected the complexity of the vessel path while minimising the number of data points to be analysed. This was a subjective, visual assessment.

With hindsight, it is likely that vessel paths were oversampled. The spatial scale of fishing behaviour that could be detected with GPS data, while many orders of magnitude finer than any previous fixing data, was much more coarse than the extremely fine scale at which vessel paths were sampled. Ryan *et al.* (2004, p219) suggest that, "as a rule of thumb tracked animals should move at least 4 m per sampling interval to avoid significant problems with sampling error and resolution". It is tempting to employ the ready accessibility of fine-scale GPS data that recent technological advances have made possible, particularly when there is a strongly

identified need for fine scale spatial fishing information, and to try to interpret tiny movements as meaningful. However, fine scale vessel movement may be an artefact of sampling error and poor resolution and will certainly be unlikely to reflect the fishing behaviour and movement of a diver underwater.

Catch per unit of distance

Catch Per Unit of Distance (CPUD) in kilograms per kilometre of distance covered defines a novel measure of catch rate relative to current time-based indices. The use of CPUD in combination with time-based CPUE showed the potential to discriminate between different fishing behaviours. For example, the relationship between CPUE and CPUD could help to characterise different fishing behaviours, as observed between divers B and C.

Catch Per Unit of Distance (CPUD) alone does not tell us much about the underwater search behaviour of a diver. Path length provides information on the amount of distance travelled by a dive vessel during a fishing event, but not about the complexity of vessel movement or tortuosity of the vessel path (Benhamou 2004). Further investigation of the relationship between boat and diver relative positions is quite essential for future fine-scale spatial monitoring of abalone fishing. The dimensions of the length of reef traversed or area searched while fishing would be valuable complimentary measurements because they describe the shape of the space within which the path was laid down. A long path of many short segments within a small area suggests a high spatial concentration of effort. A long path of fewer long segments suggests a low spatial concentration of effort. The frequency distribution of segment lengths within a path (e.g. modelled as a correlated random walk or Levy flight (Austin *et al.* 2004)) may be a better indicator of the true amount of 'distance' covered by a diver (rather than vessel) during a fishing event.

Catch per unit of area

When calculating the amount of area that is available to a diver in a day, vessel movement describes, or limits, the area that the diver can work, or could potentially have worked. The relationship between vessel movement and diver movement is undefined, and likely variable. Without measuring and defining that relationship, the largest source of error in estimating a diver's search area is likely to be the technique chosen to quantify area. Because the divers are searching a narrow band, the area fished is an unknown proportion of the area covered by the boat. A

study to investigate the relationship between diver and vessel movement would provide data for an objective selection of technique.

A scatterplot matrix of calculated daily values of A_{mcp} , A_{buf} and A_{kde} illustrated correlations between each type of area estimate (Figure 27). The weakest correlation was between A_{mcp} and A_{kde} , which reflects the different manners of calculated estimates of the area covered with these two methods. MCP and KDE area estimates are calculated in very different ways, the first encompassing area contained by a series of points and the second calculated from point density. The different levels of correlation between the three area estimates suggest that each index captures the potential search area differently.

Minimum Convex Polygons

Each of the three methods explored to quantify the amount of area searched had strengths and weaknesses. Minimum Convex Polygons are easy to generate and this type of analysis is regularly used when researching animal behaviour and looking at animal ranges; however, it is not considered to be a good measure of range (Kenward, 1987). The area of an MCP is certainly not a good estimate of area that may be searched or fished by a diver working with a vessel. Generation of an MCP doesn't allow the integration of any information about a diver's relationship or proximity to the vessel they are working from.

Buffer Analysis

Buffering a track with the length of a diver's hose and then calculating the area encompassed by the buffer gives a maximum search area available to a diver. The buffered search area estimate calculated in this chapter might be improved by changing the buffer radius to reflect diver behaviour or weather conditions. Depth data could be incorporated in calculations of buffer radius. The ArcGIS buffer calculation tool allows the radius of a buffer to be set independently for each point in an analysis. This would allow a buffer to accommodate the depth of a diver by, e.g., having a smaller radius when the diver is in deep water and a larger radius when the diver is working in shallow water. No data were collected to allow testing of the hypothesis that divers work further away from vessels in shallow water. It would be possible to vary a track buffer depending on weather conditions, e.g., Southerly weather or swell height. Under still conditions a vessel is likely to stay close to a diver (Mundy 2007) and buffer distance could be quite small. An A_{buf} that incorporates diver depth and weather information may be a better estimate of

search area than the constant buffer distance demonstrated here. The effects of weather on the vessel/diver spatial relationship are unknown and without quantifying this relationship it would be meaningless to try to do this buffering. Variable buffering and other standardisation of search area must be based on findings of how the diver/vessel relationship changes under different conditions.

Creating a variable buffer radius is more computationally intensive than performing a fixed-radius buffer around one GIS object, e.g. a line representing vessel path, as described in section 3.2.4. To create a buffer of variable radius along a path, each point along the path would need to be buffered independently and the resulting polygons merged to create one buffered area. As presently calculated, the buffer method is likely to overestimate and smooth the search area available to a diver.

Kernel Density Estimation

Kernel density estimation is a non-parametric way of estimating the probability density function of a random variable and is often used as the basis for calculating home range. Users can define search radius, grid cell size, and density contour, generating a range of different KDE's depending on the inputs chosen. This makes the method very flexible. The kernel function could be defined to weight the area around a vessel location point according to the likelihood of finding the diver in that area. A field study to investigate the relationship between diver behaviour and vessel location would provide data to inform this likelihood. Search area as estimated using the KDE was considered the most realistic by virtue of it having the least spread and so was chosen to calculate CUPA measures.

3.5.4 Amalgamation and spatial aggregation of data

Collecting spatial fishing data at the finest scale of fishing effort enabled us to calculate daily CPUE and CUPA, which were then allocated to individual fishing events. The temporal scale (daily) of catch reporting in the abalone fishery limits the allocation of CPUE to single fishing events. To define CPUE estimates at the scale of single fishing events, abalone divers would have to report catch weights at such a scale, which may not be easy to implement effectively.

There are significant, measurable differences between divers in the amount of time/distance/area that divers spend fishing. This may be a function of individual vessel (diver/deckhand) behaviours, a function of the fishing location that divers have visited and accompanying factors such as abalone abundance or weather

conditions, or both. In interpreting CPUE and CUPA measures, it is important to focus on dive site locations to see whether different divers fishing in the same area exhibit different search trends/patterns. Assuming that abundance is stable at one dive site within a window of time, the indices could possibly be standardised for abalone abundance. The remaining variability will be due to diver/deckhand behaviour and weather conditions. Alternatively, changing behaviour of one diver at the same location over time might indicate changing abundance of abalone.

CUPA as an index of availability is confounded by who was doing the fishing, and when and where the fishing occurred. When amalgamating data across different fishing locations, it becomes necessary to standardise CUPA for intrinsic differences between sites and divers. CUPA may be valid as an index of availability if applied to site and diver specifically (although there are still potential confounding factors, such as weather and algal growth). CUPA would be useful as a simple index of availability only if more data were available. Interpretation of CUPA would depend on repeated visits by individual divers to the same location over time. Upwards or downwards trends in CUPA in a single location could be compared between divers. For example, if the same downwards trend in CUPA was seen for a majority of divers visiting the same location, then that particular patch of reef could be considered to have less available abalone than previously. If the divers who have participated in this study to date continue to participate in the project then the foundations of this dataset already exist.

A KDE generated measure of CUPA, together with the traditional time-based CPUE, could be integrated into current stock assessment models and provide us with an easy and immediate indication of what is happening spatially in Tasmanian abalone fisheries while other techniques are being developed.

3.5.5 Indices reflect differences in diver behaviour

The results of analyses performed in this study have demonstrated the ability of the alternative measures of fishing effort based upon fine-scale information about fishers' behaviour to integrate the differences in individual divers' behaviour in catch-rate estimates. In particular, distance and area-based indices reacted differently to individual divers relative to traditional time-based methods.

It is essential to keep in mind that:

- (i) these results are based on a small sample size (three volunteer divers, who may not be a representative sample of the Tasmanian abalone fishery);
- (ii) preliminary analyses revealed some inconsistencies in the data recorded by the data loggers.

Even though the raw data were filtered to exclude ‘abnormal’ observations, some doubts remain regarding the reliability of the data. However, the alternative indices of abundance that have been developed in this study demonstrated the ability to better describe and account for individual diver behaviour in catch rate estimates (e.g., errors in individual’s estimates of fishing time; differences in spatial foraging behaviour underwater such as intensive harvesting of a targeted area by Diver B compared to more spatially-extensive exploitation of the resources by Diver C).

These preliminary results are based on early days of the monitoring of abalone divers fine-scale behaviour at TAFI and will require robust validation against a larger sample size (longer time series and larger number of divers) and a less error-laden dataset. It is outside of the scope of this study to rank the quality of these different indices for estimating abalone abundance, as to do so would require comprehensive knowledge of the state of the abalone population in the study area. However, further investigation could identify reliable fine-scale abundance indices to be integrated routinely in the management of the abalone fishery in the future.

The idea of ‘fishing behaviour’ is further explored in Chapter 4, where spatial indices of fishing behaviour are developed and discussed.

CHAPTER 4 MEASURES OF FISHING BEHAVIOUR: APPLICATIONS OF ANIMAL BEHAVIOUR SCIENCE

4.1 Introduction

Changes in the distribution of fishing effort are likely to be related to changes in abalone stocks, either as an agent of change or as an effect of change (Bertrand *et al.* 2004, Bordalo-Machado 2006). Developing quantitative measures of fishing behaviour will provide tools that can be used to detect changes in the distribution of fishing effort. Gorfine & Dixon (2001) ran an observing program on abalone boats working in the Victorian fishery and reported changing patterns in diver effort distribution and fishing, linked to changing diver demographics. Highlighting the relationship between diver behaviour and sustainability of a fishery, Gorfine & Dixon emphasised the importance of identifying behaviours among divers that “are desirable in terms of sustainable production”.

There are numerous studies looking at quantitative analysis of movement and distribution of target fish species, but only a few have examined the behaviour of fishers. Specific examples include:

- Peruvian anchovy trawl fishery (Bertrand *et al.* 2004)
- Tuna/pelagic fishing fleet (Caddy and Carocci 1999)

Studying vessel movement during a fishing event investigates effort distribution at an individual scale, in response to environmental features (Johnson *et al.* 2002) including presence of fish (Bertrand *et al.* 2004). In the field of animal behaviour science it has been demonstrated that the scale of forager movement can be relative to the scale of prey distribution (Marell *et al.* 2002, Austin *et al.* 2004, Ramos-Fernandez *et al.* 2004, Bertrand *et al.* 2005). One of the novel components of this study is that animal behaviour tools have not previously been used to analyse GPS data collected from artisanal or small-vessel fishers.

4.1.1 What is ‘fishing behaviour’?

The description and monitoring of abalone fisher’s ‘fishing behaviour’ has two separate components: the behaviour of the diver in the water (i.e. path traversed, depth and dive duration) and the pattern of movement of the dive vessel. Typically the behavioural decisions of the deckhand driving the boat (i.e. vessel location) will be subordinate to those of the diver in the water. Both diver and deckhand

behaviour might be influenced by multiple factors including abalone abundance (Beinssen 1979, Gorfine and Dixon 2001), reef type and algal abundance (Beinssen 1979), wind strength and direction, water temperature, depth of available abalone, swell and current (Mundy 2007), quota available and possibly by instructions from abalone receivers/processors or quota holders (i.e. selective fishing). The fishing behaviour that is expressed is a result of several of these environmental variables on the day of fishing, and of the individual work habits and behavioural preferences of both the diver in the water and the deckhand operating the vessel.

Fishing behaviour can be described and quantified at nested spatial and temporal scales.

- A. *Searching Behaviour*: Behaviour during a fishing event can be explored by quantifying patterns of movement during a single fishing event and generating movement parameters that describe effort distribution at a very fine scale
- B. *Behavioural Indicators*: Fishing behaviour can be summarised and quantified at the scale of each fishing event by generating descriptive statistics, for example, fishing depth, fishing event duration, area fished or a single index of behavioural complexity.
- C. *Fleet Behaviour*: At the largest spatial scale the aggregated behaviour of the fleet across the whole fishery can be quantified, for example, by mapping the distribution of fishing effort in hours over the entire fishing ground. Effort can be mapped annually, seasonally, or at other temporal scales.

Capturing fishing behaviour with fine scale data

Fishing behaviour incorporates deckhand behaviour, vessel movement and diver behaviour. When quantifying fishing behaviour in this study, estimates of behavioral parameters (i.e. effort distribution) were based upon vessel movement and calculated using GIS tools. In the absence of quantitative data describing the relationship between a diver and their vessel, it was assumed that vessel position approximated the diver position.

Data collection methods are covered in detail in Chapter 2. Depth loggers worn by divers captured entry and exit from water and recorded a chronological depth profile of a given fishing event. Typically divers fish more deeply in rough conditions to avoid physical injury or damage to vessels. Effort is more concentrated in deeper

waters on the West coast than the East coast of Tasmania (Tarbath *et al.* 2007). GPS loggers capture vessel movement data. The trace of the vessel path provided by the GPS logger is an interesting visual representation of a fishing event and captures information about the behaviour of a vessel. However, a fishery requires objective quantitative descriptors of each fishing event to maximise the benefit of the spatial information.

4.1.2 (A) Searching behaviour: quantifying complexity of behaviour during a fishing event

GIS data analysis techniques can be applied to paths of abalone fishing vessel movement. These techniques quantitatively describe fishing behaviour at the scale of individual fishing events, generating performance metrics that might be useful for assessment of small-vessel fisheries such as Australian abalone fisheries.

Indices and metrics to characterise spatial complexity in effort distribution

The field of animal behaviour science offers a wide range of analyses that have been used to quantitatively describe patterns of movement and distribution of foraging effort. These tools include:

- *Bivariate Kernel density functions*

Bivariate Kernel density functions are used to calculate an estimate of the density of points in a space, and are generally applied in animal behaviour studies to estimate an animal's 'home range' (Hooge 1999). In a novel application, the ratio of 50 and 95% density contours is proposed here as an index of spatial heterogeneity of effort.

- *Analyses of rates of movement*

Analyses of rates of movement are used to relate the scale of animal movement to the scale of the landscape in which animals forage, for example, caribou in woodlands and bettongs in sclerophyll vegetation (Vernes and Pope 2001, Johnson *et al.* 2002).

- *Step-length frequency analyses and Lévy flights*

Step- frequency analyses and Lévy flights are used as measures of searching efficiency. Lévy flights are a class of random walks whose step lengths fit into a probability distribution with a power-law tail (Viswanathan *et al.* 1999). Applications of Lévy flights in behavioural analyses build on the concept of rates of movement.

- *Sinuosity and fractal dimension*

Sinuosity and fractal dimension are used to quantify the tortuosity of a search path and to investigate the scale dependence of foraging behaviour, by looking at steps of change in fractal dimension complexity within a path, e.g. the foraging behaviour of deer and goats (sinuosity) and wandering albatross (fractal dimension) (Etzenhouser *et al.* 1998, Fritz *et al.* 2003).

4.1.3 (B) Behavioural indicators: quantitative summaries of behaviour for whole fishing events

Fishing duration and diver depth as measures of fishing behaviour

Dive duration is a basic component of fishing effort in abalone fisheries, but historically, the number, duration, and depth profile of individual fishing events have never been recorded. Effort data are typically estimated as total effort pooled for each calendar day of fishing, or more recently as effort spent in three depth bands (0-10 m, 10-20 m, > 20 m). A consequence of the pooling of effort across multiple fishing events is that the behavioural component of multiple dives, dive duration and depth profile are lost. The opportunity to electronically record the time of diver entry to and exit from the water provides a far more accurate measure of dive duration than the number of dives per calendar day. The depth profile may also be considered a one-dimensional spatial measure of diver behaviour. These descriptions of diver activity can be considered independently from the movement of the vessel.

4.1.4 (C) Fleet behaviour: the phenomena of Ideal Free Distribution

Ideal Free Distribution is a theory that animals will distribute themselves among several patches of resources proportionately to the amount of resource that is available in each area. The theory of Ideal Free Distribution has been applied as a fisheries management concept (Prince & Hilborn 1998; Gillis 2003; Branch *et al.* 2006). Chapter 3 explored techniques that can be used to apply traditional temporal catch rate measures at fine spatial scales appropriate to a fishery of metapopulations, and investigated applications of GIS techniques to incorporate spatial measures of effort such as search area into catch rate indices. Catch Per Unit of Distance and Catch Per Unit of Area indices were generated. However, CPUE based stock assessment methods rely upon the assumption that there is a relationship between target species abundance and catch rate. The dynamics of this relationship are not clearly defined and have been strongly questioned in

literature (Atkinson *et al.* 1997, Karpov *et al.* 2000, Gorfine and Dixon 2001, Leiva and Castilla 2001, Branch and Clark 2006, Branch *et al.* 2006). Although there are concerns about the validity of CPUE as a measure of abundance, CPUE is a widely used to estimate the abundance of marine resources in many fisheries. A strong case for continued use of CPUE as a valuable indication of abundance in abalone fisheries has been advanced (Chick *et al.* 2008), subject to recognized limitations. In particular, standardised catch per unit effort is used in the management of all Australian abalone fisheries and is uniformly accepted as a valid assessment tool (Worthington *et al.* 1998, Maunder and Punt 2004, Tarbath *et al.* 2005, Hart *et al.* 2009).

CPUE is surprisingly homogenous across the Tasmanian abalone fishery excepting the west coast which is relatively inaccessible and difficult to fish (Prince and Hilborn 1998). The spatial homogeneity of CPUE is explained by the phenomena of Ideal Free Distribution (IFD) which predicts that when fishers have a perfect knowledge of fish abundance, and when there is no cost associated with choice of fishing ground, then the desire of fishers to maximise their profitability will mean that profit rates (roughly equivalent to catch rates) will be equal in all areas (Gillis 2003). A diver will not fish in a location if they could be fishing more profitably elsewhere. Thus, the *amount* of fishing effort expended (number of dives or hours spent diving) in each area will reflect abundance better than catch rate (CPUE or CPUT) (Branch *et al.* 2006).

4.1.5 Objectives

Quantifying patterns of movement is a shift from the study of static distribution of effort during a fishing event (Chapter 3) and towards a study of the functional response of fishers to their environment. In this chapter I apply methods used in the field of animal behaviour science to quantify and characterise spatial effort distribution across multiple fishing events and within individual abalone fishing events. I test the suitability of various spatial analysis techniques from the field of animal behaviour science to quantitatively identify fishing behaviours of divers by using data collected with GPS loggers during fishing. I discuss quantitative behavioural performance indices in the context of interpretation and the identification of 'desirable' and 'warning-flag' behaviours.

The objectives of this chapter are to:

- a) describe measures of *fishing behaviour* (duration of fishing events, diver depth and rates of movement) and demonstrate the value of these measures in fisheries assessment;
- b) identify GIS tools that can be used to quantify spatial elements of fishing behaviour during a fishing event;
- c) demonstrate the application of these tools to
 - calculate descriptive metrics for vessel paths e.g. mean distance per segment, fractal dimension of the path;
 - calculate other quantitative statistics describing diver behaviour.

4.2 Methods

4.2.1 Spatial complexity of fishing behaviour: Area-based

Measures

A homogeneous distribution of fishing effort during a fishing event is here considered to be a uniform pattern of movement while fishing, characterised by a regular rate of movement over fishing grounds. Non-homogenous effort distribution would be characterised by stop-and-start behaviour, leading to disjointed aggregations of GPS positions within a search contour polygon.

Kernel Density Index: spatial homogeneity of effort within fishing events

A bivariate normal KDE was calculated for each separate fishing event recorded for this study, and 50% and 95% probability polygons were identified (Figure 33). The methods used to calculate the KDE values are described extensively in section 3.2.4 “Kernel Density Estimation”. The 50% contour is considered to represent the ‘core’ area of a home range in animal behaviour studies, and the 95% contour is a conservative approximation of the area utilised, serving to remove outlier points (Worton 1989, Selkirk and Bishop 2002).

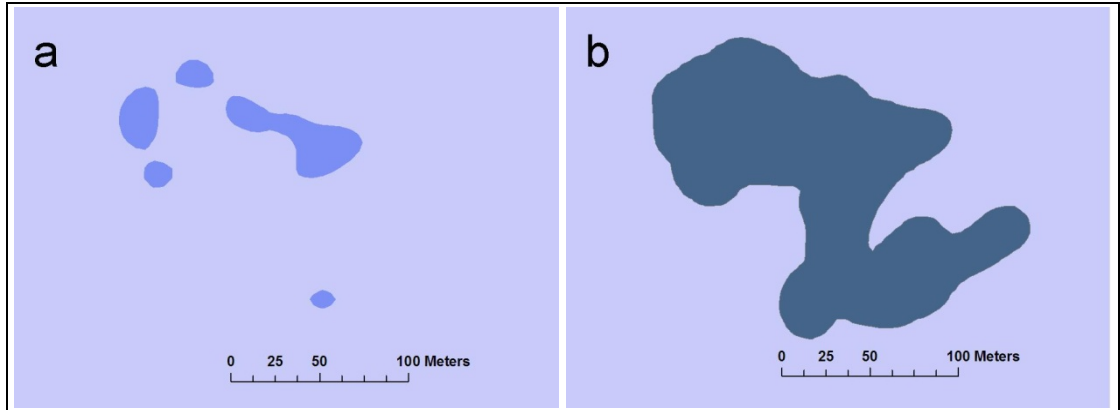


Figure 33. The concentration of vessel location points for a single fishing event can be described by finding the ratio of the area contained within the 50% contour of a KDE raster surface (a) to the area contained within the 95% contour (b). Cf. Figure 18.

The ratio of the area of the 50% polygon to the 95% polygon (Eq. 6) was calculated as a measure of the homogeneity of spatial distribution of fishing effort at any time during a fishing event. The 50%/95% ratio is referred to hereafter as the Kernel Density Index (KDI).

$$KDI = KDE50 / KDE95 \quad \text{Eq. 6}$$

Where $KDE50$ is the area contained within the 50% contour of a KDE raster surface in m^2 and $KDE95$ is the area contained within the 95% contour of a KDE raster surface in m^2 . To the best of my knowledge, this ratio has not been used before as an index of homogeneity.

Kernel Density Estimates with 50 and 95% contours were generated for 985 separate fishing events recorded by three abalone divers between July 2005 and April 2007. Kernel Density Index values were calculated for 982 fishing events.

Hypothetically, if abalone are distributed evenly and fishing effort is also even, then the KDI should be approaching 0.526 (i.e. $0.5/0.95 = 0.526$) given an optimal set of parameters for the KDE operator. As abalone distribution becomes sparser or more scattered the KDI should be substantially less than 0.5 since the diver is more mobile underwater. As a consequence, the extent of the wider potential search area (associated with the 95% probability distribution) becomes more important relative to the extent of the 'core area' (associated with the 50% probability distribution). Conversely, when working on a high-density patch of abalone, the ratio would be

expected to be higher than 0.5, as both 50% and 95% contours of probability distribution should tightly match the given patch. The ratio should tend towards 1 as diver stays in the same hotspot for the duration of the dive.

Calculated at the end of a fishing event, KDI is a single value that describes the distribution of fishing effort across the whole event. However, when calculated incrementally during a fishing event KDI changes as a factor of changing fishing behaviour during a dive. Note that a fishing event of short duration has few location points, and each point carries a lot of weight when calculating KDEs relative to long fishing events with many data points, which individually contribute to a lesser extent to the calculation of KDEs. Thus, the weight of each location point diminishes as a fishing event becomes longer and more points are recorded. The relationship between KDI and fishing event duration was illustrated by generating KDIs for vessel paths of varying duration. The frequency distribution of KDI was tested for log-normal fit using the Kolmogorov-Smirnov-Lilliefors (KSL) goodness-of-fit test. A quantile box plot was drawn to show the median, sample mean with 95% confidence interval and outliers outside of the upper (lower) quartile ± 1.5 times the interquartile range. Cumulative KDI was calculated to evaluate the potential of this Index to identify effort 'hotspot' locations.

Rate of change of KDI during a fishing event is more informative than cumulative KDI. The progressive effects of dive duration on KDI were simulated using a single fishing event with a low KDI as a case study. The dataset of vessel location was divided into 10 minute sub-samples and KDEs were generated in cumulative 10 minute increments, starting with the first 10 minutes of the dive and progressing to the full duration. Change in KDI (y-axis) was plotted against increasing dive duration (x-axis).

4.2.2 Spatial complexity of fishing behaviour: Line-based Measures

The pattern of the vessel path during a fishing event potentially contains useful spatial information that can be characterised, and used as a quantitative measure of each fishing event. Several possible analytical methods have previously been applied to animal path analysis, and/or analyses of large vessel VMS data. The methods considered here include step-length frequency (as used by Viswanathan *et al.* 1999), fractal dimension (Fritz *et al.* 2003) and sinuosity (Etzenhouse *et al.*

1998). These measures use the distance between sequential points as the basis for analysis. While a number of line-based indices were evaluated, they were immediately discounted as a viable metric for characterisation of the complexity of fishing events. Results of the analyses are not presented, nevertheless, the methods used are described and reasons for rejection are provided in the Methods. The weaknesses of some line-based methods are also reviewed in the Discussion (4.4.2 'Spatial complexity of fishing behaviour: Line-based Measures').

Creating a Vessel Path from Point Data

To digitise the path of a continuously moving vessel, the spatial coordinates of the vessel were recorded at regular time intervals as described in section 2.2.2. Within each fishing event, successive positions were connected with straight lines to represent the vessel path. This process has been described in more detail in section 3.2.3. Displacement during the regular 10-second time interval is called a 'step'. The portion of line between sampling positions along the linear path is called a 'line segment'. One line segment was created for each step of the vessel path.

Rates of Movement

Rate of movement (or velocity) for the vessel during a fishing event was calculated for each step of the vessel path and the mean calculated for the full length of the path. Step length was calculated for each line segment of each digitised vessel path using the 'Calculate Movement Parameters' function in Hawth's Analysis Tools (Beyer 2004). Mean vessel velocity (V) during each fishing event was calculated as:

$$V = L_t / n \quad \text{Eq.7}$$

Where: L_t is the total length of the vessel path and n is the number of steps (i.e., 10 second intervals) that make up that path. These values of mean vessel velocity were plotted against Eastings. Frequency distributions of mean vessel velocity were plotted for each diver (A, B and C) and for the aggregated east and aggregated west coast fishing events. The non-parametric Kruskal-Wallis one-way analysis of variance (Kruskal and Wallis 1952) was used to test for equality of medians in data grouped by diver (A, B and C) and grouped by location (east and west coast of Tasmania).

Attempts were made to describe searching behaviour within a fishing event using estimates of fractal dimension to identify scales of change during fishing activity. These efforts were discontinued for two reasons:

- The fine-scale movement of divers is masked by the movement of the vessel, and searching patterns cannot be assumed to be visible in a vessel track. While sinuosity and fractal dimension analyses are potentially interesting, for them to be applied as measures of foraging behaviour information on movement of the diver, rather than the vessel, is required.
- There is some contention about the validity of using fractals to describe animal movement, with claims that the fractal analysis of paths is only liable to generate artificial results (Benhamou 2004).

Sinuosity as a measure of path complexity

This study used the Hawth's Analysis Tools formula for calculating sinuosity of vessel paths. This is a very simple measure of sinuosity and is typically applied in studies of fluvial processes (Mueller 1968). This method considers the distance travelled between start and end point and compares it to the most direct straight line between start and end point, but does not take into consideration the number of turns, the angle of turns or the length of steps taken along the path. Benhamou (2004) recommends an alternative method for calculating 'sinuosity' when wanting to reliably estimate tortuosities of a random search path. He recommends a sinuosity index which combines the mean cosine of changes of direction with the mean step length.

As applied in Hawth's Analysis Tools version 3.21 for ArcGIS (Beyer, 2004), a sinuosity index is a simple measure of path complexity calculated as:

$$S = L_t / d \quad \text{Eq. 8}$$

Where: L_t is the total length of the line and d is the straight line distance between the start and end points of the path. The value of path sinuosity was calculated for each fishing event in the dataset, and these values were plotted as a frequency distribution.

Fractal Dimension of vessel path

A fractal dimension attempts to summarise a potentially complex two-dimensional pattern (the vessel path) using a single statistic to describe how ‘complicated’ a self-same figure is. The calculated statistic will range between 1 (a straight line) and 2 (maximum tortuosity covering a plane entirely). Fractals were calculated using two different software tools; Hawth’s Analysis Tools (Beyer, 2004), and the ‘Dividers’ method using Fractal 5 software package (Nams 2006).

Fractal Dimension using Hawth’s Analysis Tools

The Line Metrics tool provided with Hawth’s Analysis Tools (Beyer, 2004) uses a simplified formula to estimate the fractal dimension of a path. In this instance it is calculated from a consideration of the number of line segments (n), the straight line distance between the start and end points of the path (d), and the total or actual length of the path (L_t). Thus, for each path, the fractal dimension (D) is estimated (using natural logarithms):

$$D = \log(n) / (\log(n) + \log(d / L_t)) \quad \text{Eq. 9}$$

A value of path fractal dimension was estimated within the ArcGIS environment using this method, for each fishing event in the dataset and these values were plotted as a frequency distribution.

The Fractal Dimension D can be calculated very rapidly using Hawth’s Analysis Tools and the process is almost fully automated. However, the estimate of D achieved with this formula is not robust under some conditions. When the start and end locations of a track are very close together (d is small) and the track length is proportionally very long (L is large), D achieved values greater than 2, and even greater than 3. For a strict fractal dimension this would be impossible; a D value of 2 would imply that all space in 2 dimensions is occupied and a D value greater than 2 would necessarily be occupying a 3rd dimension. For this reason, the Fractal Dimension calculated using Hawth’s Analysis Tools was rejected.

The ‘Divider’ Method of Calculating Fractal Dimension

In animal behaviour studies, fractal dimension is traditionally measured using a technique known as the ‘divider’ method, described by Dicke and Burrough (1988), which involves walking a pair of ‘dividers’ of defined interval along a path and calculating a fractal dimension at each step, then calculating an overall fractal

dimension for the full length of the path (Nams 1996). This promising method for calculating Fractal Dimension does not operate in an ESRI GIS environment, but was calculated using the Fractal 5 software package (Nams 2006), available as freeware from <<http://www.nsac.ns.ca/envsci/staff/vnams/fractal.htm>>. This program has been used for generating values of fractal dimension for a number of peer-reviewed papers on animal behaviour and track tortuosities (Fritz *et al.* 2003) and generates a more robust estimate of fractal dimension than that calculated using Hawth's Analysis Tools.

Values of Fractal Dimension calculated using the 'divider' method were rejected for interpretation as behavioural indices because of reasonable doubts about the validity of applying fractal analysis to animal (and by extension, fisher) paths (Turchin 1998, Benhamou 2004). While fractals can adequately describe the complexity of landscapes for example, they do not apply to most animal foraging behaviours. Living organisms forage at ecological scales proportional to their body size and mobility. Therefore, they are highly unlikely to forage across a range of temporal and spatial fractal dimensions.

4.2.3 Behavioural indicators: quantitative summaries of behaviour for whole fishing events

Fishing Duration

The duration of a fishing event, in minutes, was calculated from data collected at 10 s intervals (see Chapter 2 for more detail). Data were collected by three divers, A, B and C. As described in Chapter 2, the GPS dataset was filtered for records where depth was greater than 0.5m and a diver was considered to be fishing at all times when depth was greater than 0.5m. Fishing duration was plotted as a frequency distribution a) for each individual diver, b) for each of east and west coasts (all divers combined) and c) for all fishing events included in this study. The nature of these distributions was tested to determine whether the distribution of the duration of fishing events was bimodal, as a reflection of two major types of events: short-duration unsuccessful events versus longer successful fishing events.

Diver Depth

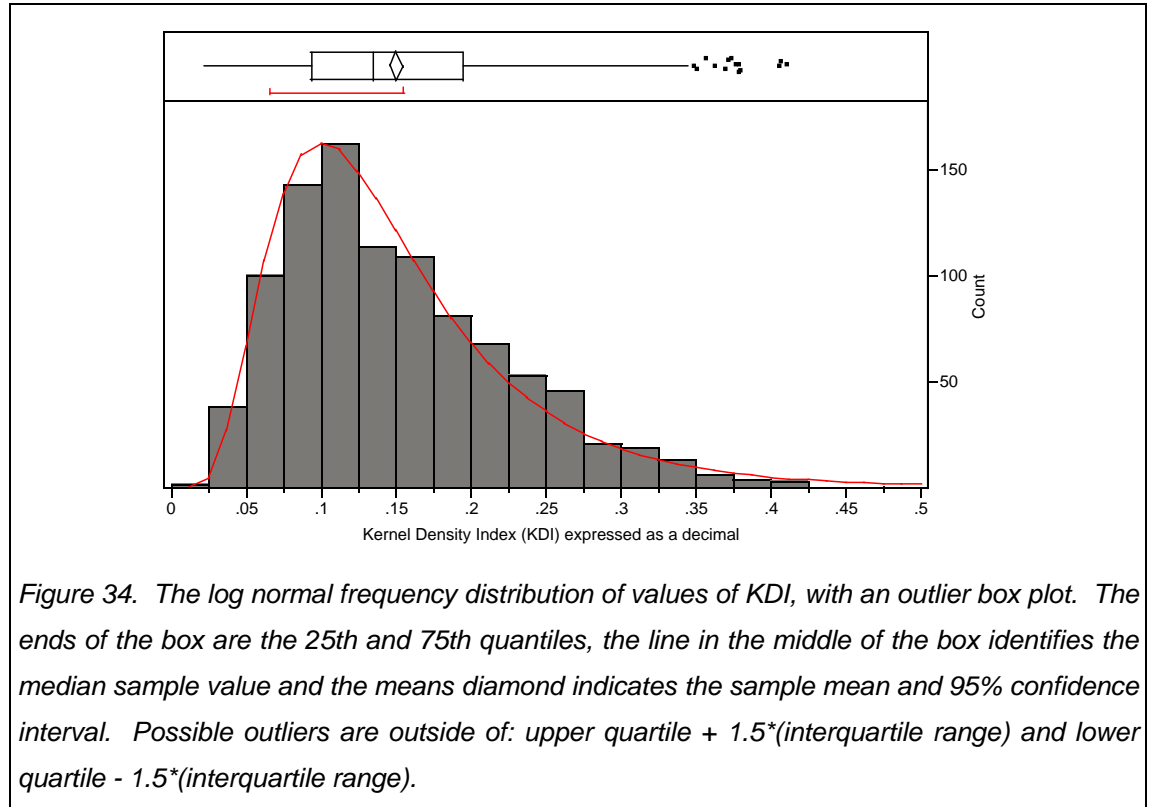
Depth record data collected by the three divers in this study were analysed either pooled together, per diver, or per fishing event. Mean fishing depth was calculated

for each fishing event. Due to the higher wave exposure on the west coast, fishing events are widely assumed to be deeper on average on the west coast than on the east coast (Mundy 2007). To identify broader spatial patterns in diving depth of abalone fishers, the mean depth was plotted against an x-axis of Eastings for the west coast and for the east coast of Tasmania. Frequency distributions of depth for each coast were tested for normality using the Shapiro-Wilk test (Shapiro and Wilk 1965), and for lognormal fit using the KSL (Kolmogorov-Smirnov-Lilliefors) goodness-of-fit test (Lilliefors 1967). A two dimensional surface of effort distribution by depth and longitude was contoured at 5% density quantiles for each of the west and east coasts.

4.3 Results

4.3.1 Spatial complexity of fishing behaviour: spatial homogeneity of effort

Three events were excluded because of KDE processing errors. Frequency distribution of values of KDI for all fishing events is lognormal (Figure 34) (KSL $D=0.034$ and $\text{Prob}>D=0.0100$). The lowest KDI value was 0.023, highest (approaching homogenous effort distribution of 0.526) was 0.411 and the median was 0.135.



Fishing events with KDI values falling below the 10% quantile (0.068) were classified as having 'low' KDIs (Contour maps in Figure 35a, 36b, 36c), values falling above the 90% quantile (0.258) were classed as having 'high' KDIs (Figure 35g, 36h, 36i) and values ranging between these quantiles were classified as having 'medium' KDIs (Figure 35d, 36e, 36f; see also Table 9). Fishing duration is a true proxy for the number of location points recorded (n) because GPS sampling was at regular 10 second intervals.

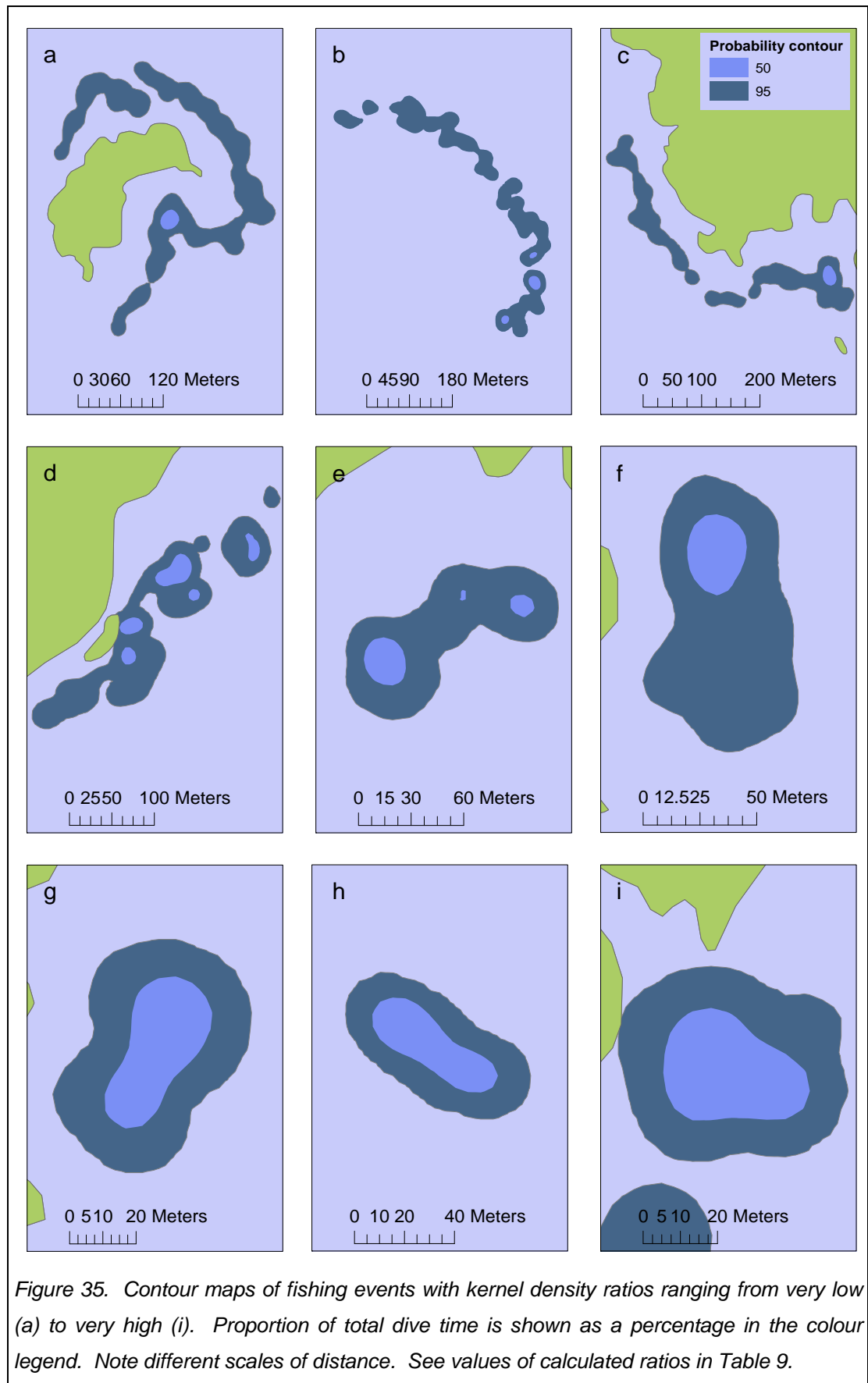
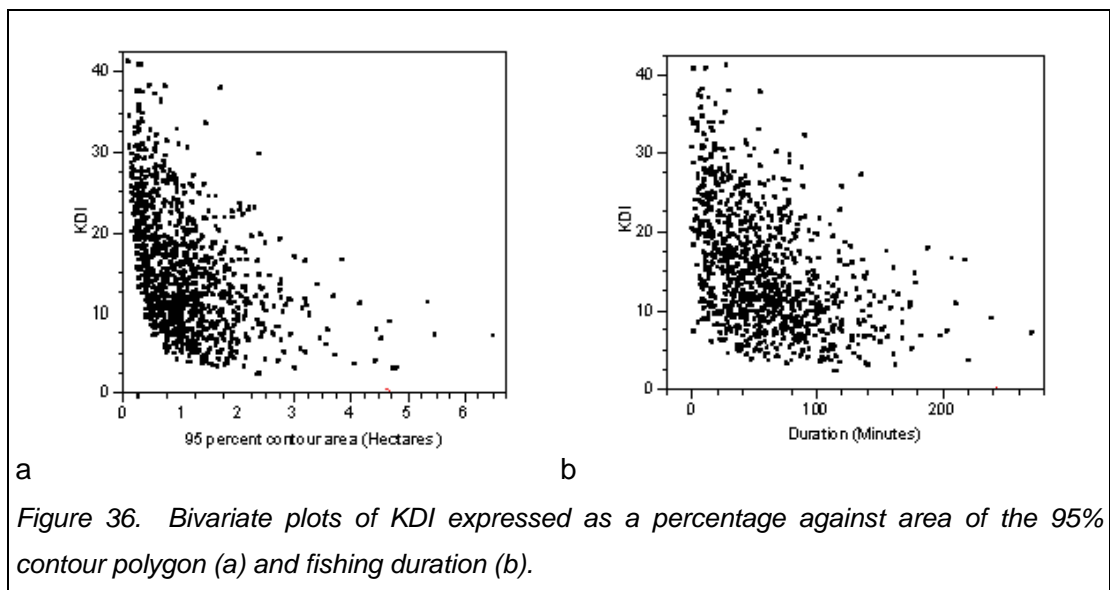


Table 9. Calculated KDI for the fishing events in Figure 35 (a to i): n = the number of location points recorded. A low KDI (e.g. <0.05) indicates that half of the fishing event was spent in a small part (e.g. $<5\%$) of the total area covered during the dive, and thus that effort distribution was heterogeneous.

	KDI class	n	KDI	fishing duration (minutes)	95% area (metres ²)	50% area (metres ²)
a	low	690	0.023	115	23996	564
b	low	852	0.031	142	30433	949
c	low	624	0.034	104	17886	614
d	medium	252	0.118	42	18874	2220
e	medium	336	0.118	56	6153	727
f	medium	300	0.118	50	5664	669
g	high	108	0.302	18	2893	874
h	high	30	0.336	5	2691	905
i	high	144	0.338	24	2671	901

Dives of longer duration tend to have lower KDIs (Table 9 and Figure 36b). Short fishing events had both small and large KDIs, whereas longer fishing events always had a small KDIs (when duration >200 min, KDI <0.2). The relationship between KDI and KDE95 area was also not linear (Figure 36a). ‘Small’ fishing events (those that covered a small area) had both small and large KDIs while ‘large’ fishing events had only small KDIs. KDIs quantify the relationship between fishing event duration or ‘size’ and the degree of heterogeneity of effort distribution during the event. The longer a fishing event, and the larger the area that was covered during the event, the less homogenous the distribution of effort during that event.



Utility of cumulative Kernel Density Index and Duration to identify effort 'hotspots' within a fishing event

Analysis of a single fishing event for KDI value with increasing time steps of defined duration has isolated brief periods of high effort spatial concentration within a predominantly homogenous search path. This dive is also shown in Figure 36b. Figures 36a and c also show long distance dives with small areas of slow movement. In the example in Figure 37 fishing effort was concentrated to the beginning of the fishing event, with 50 percent of event duration spent in 3 percent of the total area at the conclusion of the dive (KDI of 0.031 at 142 minutes). The 50 percent density contour was completely contained within the first hour of the 140+ minute dive (Figure 37f, c.f. Figure 37i). The low KDI of the dive reflects the high vessel speed for part of the dive. See Appendix 3 for data tables and all contours in 10 minute increments.

The slope of the line segments between successive KDIs is related to the rate of search area increase (Figure 38). A peak in the plot indicates that the vessel stopped moving or spent a lot of time in a small area, and a continual decline in KDI with duration indicates that during that period a vessel covered a steadily growing area.

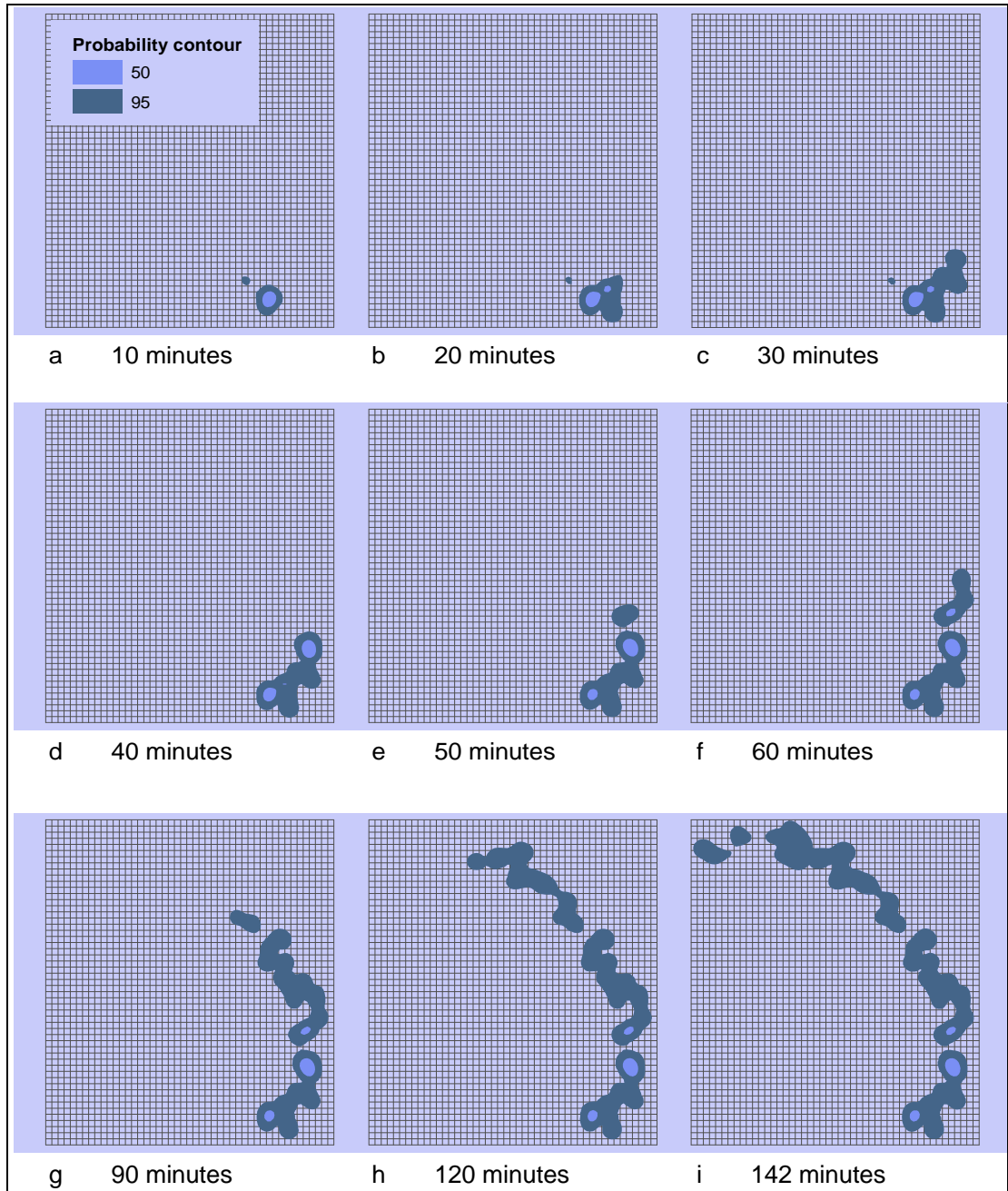


Figure 37. KDE 50 and 95 percent contours for a single dive, representing changes in KDI from 10 minutes after start (a) until the end of the dive (i) at 142 minutes. Contours overlay a 5 metre scale grid. See Appendix 3 for data tables and all contours in 10 minute increments. The KDI values for these increments are plotted in Figure 38.

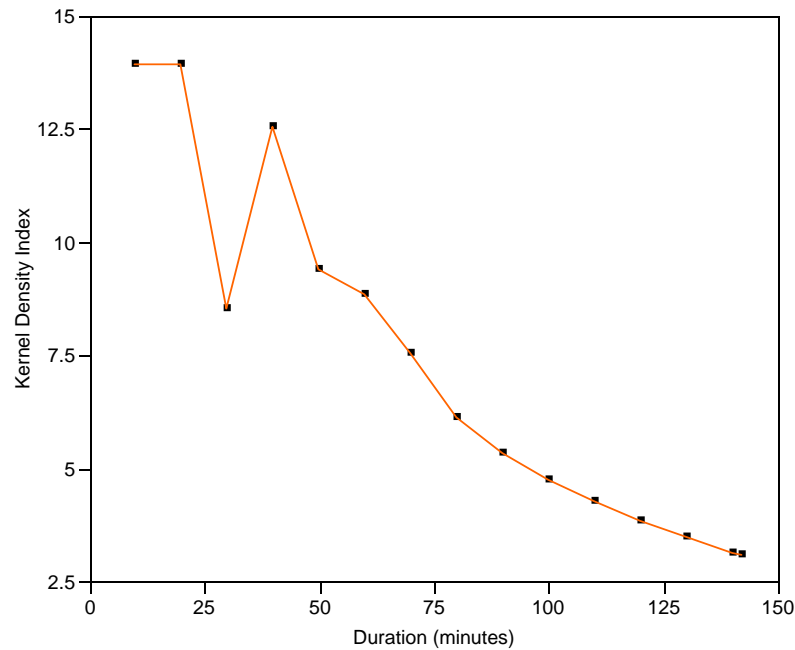


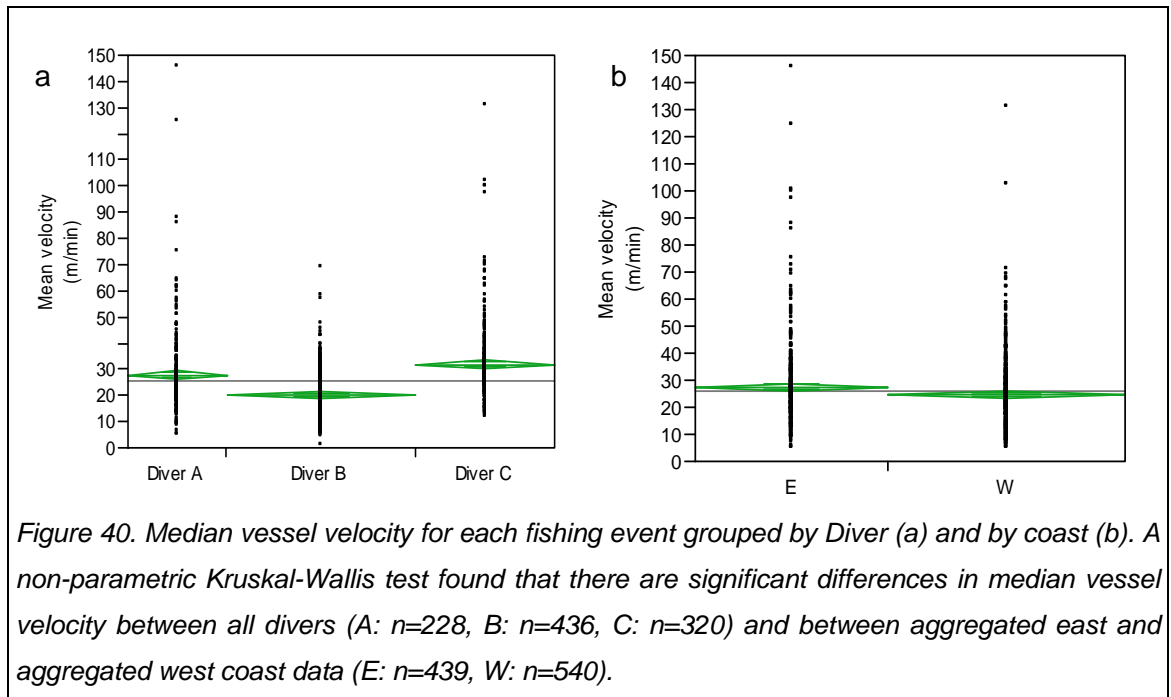
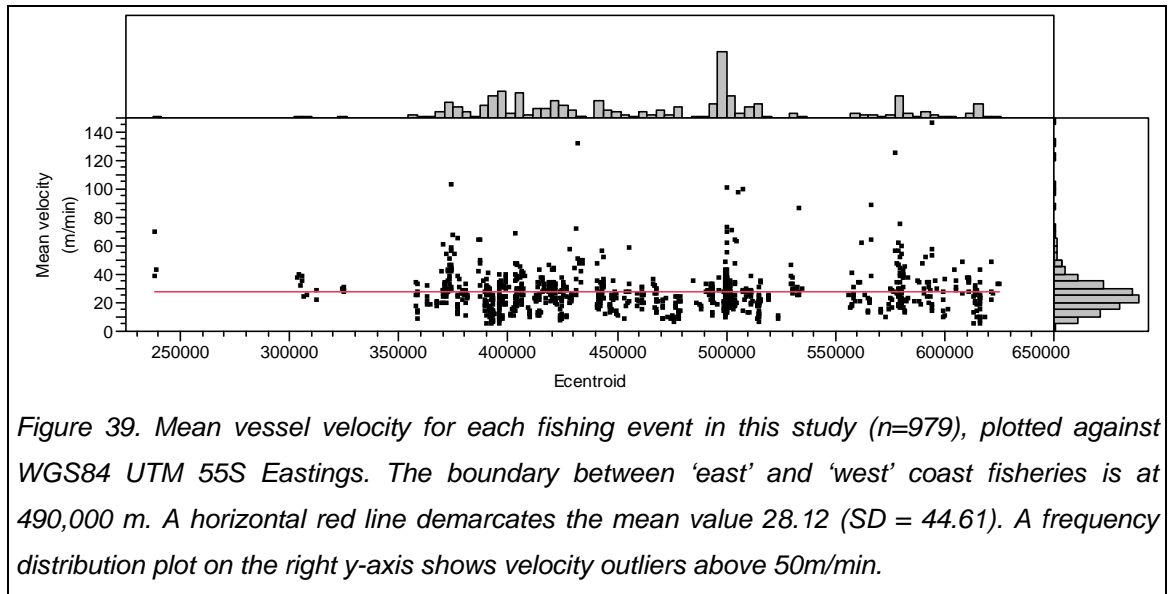
Figure 38. KDI values as percentages, simulated from a single fishing event by dividing the event into 10-minute segments. KDE 50 and 95 percent contours were generated for each cumulative 10-minute fraction of the dive (C.f. Figure 37). These are data at a scale finer than even single fishing events, and can be used to differentiate between periods of rapid movement and slow movement during a fishing event.

4.3.2 Spatial complexity of fishing behaviour: Line-based Measures

Rates of Movement

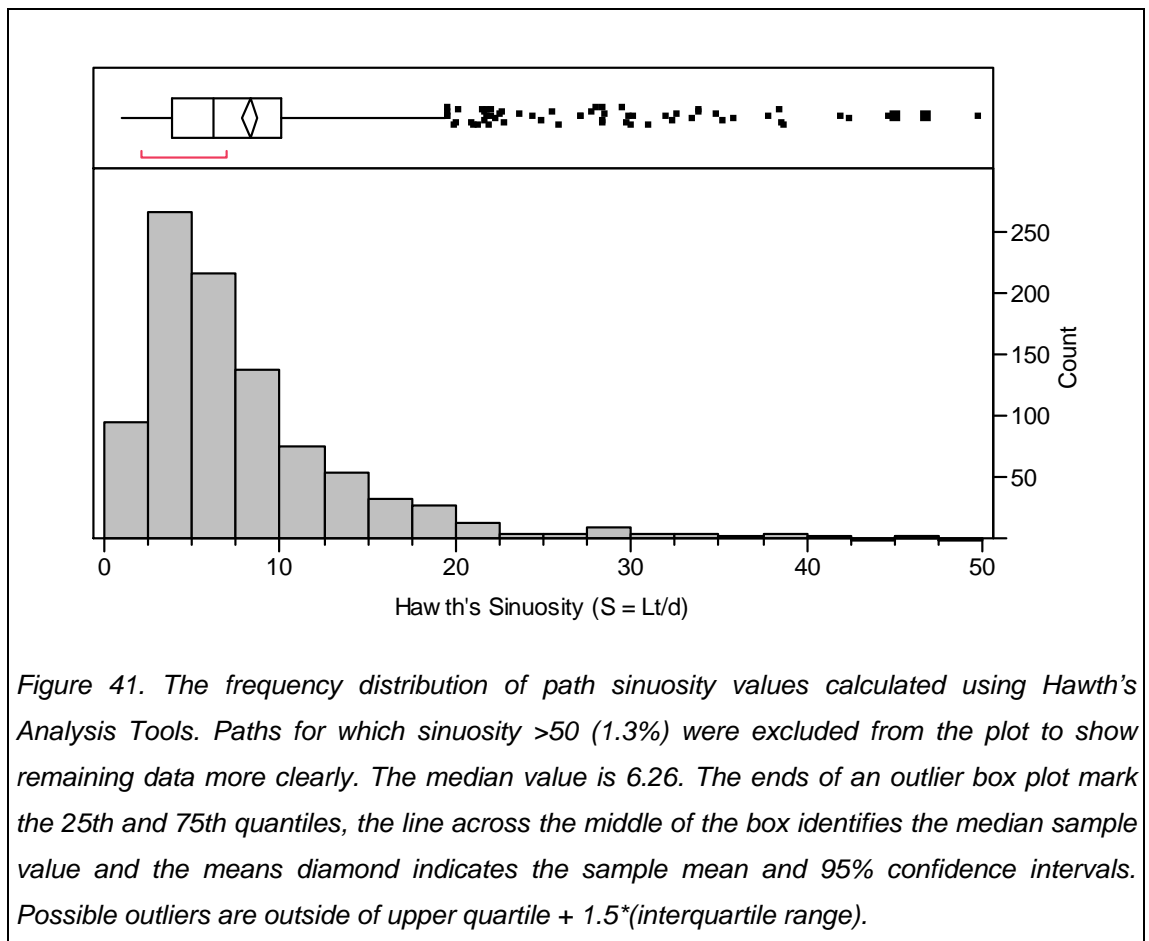
Mean vessel velocities (rates of movement) for each fishing event in this study (n=979) were concentrated between 10 m/min and 50 m/min, with a grand mean of 28.12 m/min (SD = 44.61). A small number of mean velocity rates were greater than 50 m/min with one extreme value of 145.11 m/min likely due to GPS error or to vessel speed being much greater than diver speed. These values are shown plotted against easting Cartesian coordinates (WGS84 projection, UTM zone 55S) in Figure 39. The boundary between 'east' and 'west' coast fisheries is at 490,000 m. A non-parametric Kruskal-Wallis test found that there were significant differences in median vessel velocity between all divers ($P < .0001$) (Figure 40a). The median rate of vessel movement for Diver A was 27.9 m/min, Diver B was 21.5 m/min and Diver C was 37.5 m/min. The higher vessel speeds (e.g. those >50m/min) would be unlikely speeds of movement for a scuba diver. These high

speeds suggest that vessel speed is not a reliable proxy for diver speed. There were also significant differences in median vessel velocity between aggregated east and aggregated west coast data ($P=.0025$) (Figure 40b). The differences between east and west coast velocities were small, with a median rate of movement on east coast of 27.3 m/min and west coast of 28.9 m/min. The small degree of difference between east and west coasts makes it unlikely to be meaningful despite being statistically significant.



Sinuosity from Hawth's Analysis Tools

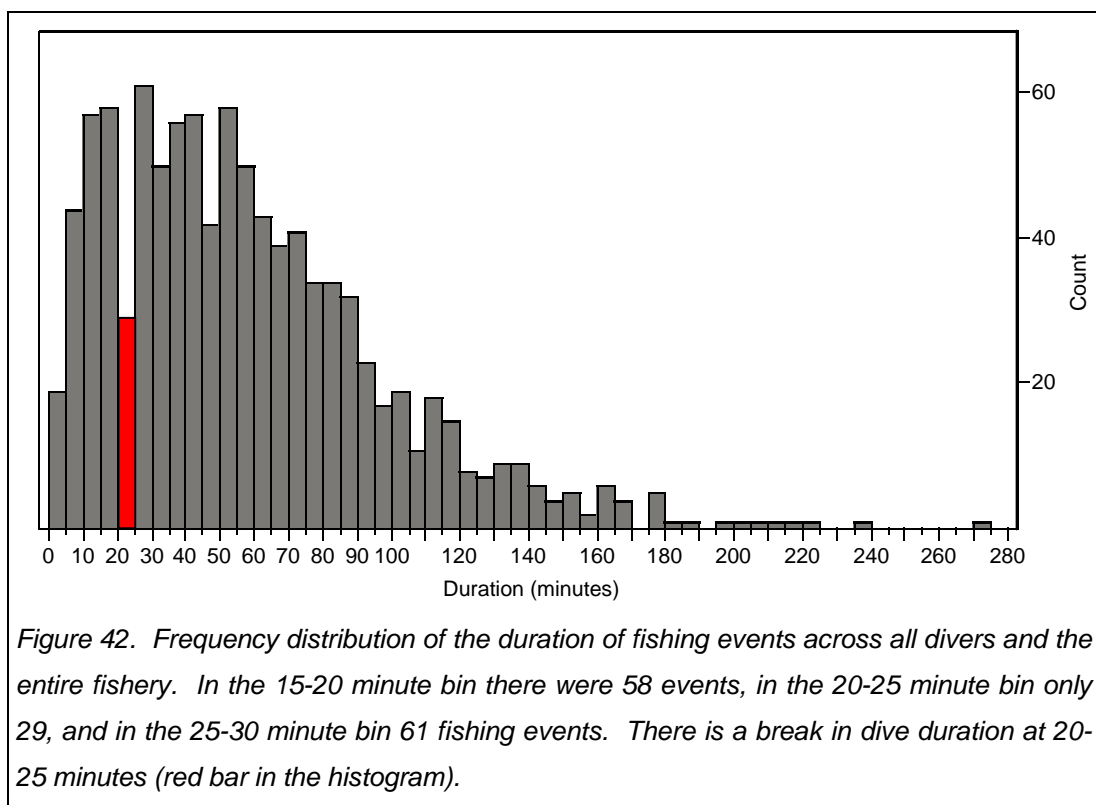
Sinuosity is a measure of path complexity, or tortuosity. The Hawth's Analysis Tools formula for calculating sinuosity of vessel paths (see section 4.2.2 'Sinuosity as a measure of path complexity') returned values of sinuosity between 1.001 (least complex, almost straight line) and 228.941 (most 'sinuous', or complex). The frequency distribution of sinuosity values across all divers (A, B, C) in the study is shown in Figure 41 ($n = 989$). Paths for which sinuosity >50 ($n = 22$) were excluded from the plot to show remaining data more clearly. The median sinuosity value was 6.26, meaning that the distance the vessel travelled from the start to the end of the track was 6.26 times further than the straight line distance between those two points. However, this measure of sinuosity includes no measure of the distribution of that path between the points. For example, the vessel may have followed a triangular path from start to a remote point, to end of the track, or may have taken very many short steps around the start location before travelling directly to the end point.



4.3.3 Behavioural indices: quantitative summaries of behaviour for whole fishing events

Dive Duration

There is a distinct break in the frequency distribution of the duration of fishing events at the 20-25 minute bin, which had approximately 50% of the number of fishing events of either of the adjacent bins (15-20 or 25-30) (Figure 42). Across all divers, 21% of fishing events had a duration of <25 minutes (211 events, $n=982$). The same pattern of separation between dives shorter than 25 minutes and longer than 25 minutes was observed when frequency distributions of dive duration were separated by diver, and by east/west coast (See Appendix 2 for frequency distributions for each of these classes). The majority of fishing events were between 25 and 100mins, with 65% of fishing events falling in this band.



Dive depth

The mean diver depth in metres for each fishing event was plotted against GPS derived eastings (geographic Cartesian coordinates, WGS84 UTM zone 55S) for the west ($n = 550$) and east ($n = 439$) coasts separately (Figure 43 and Figure 44). Mean and maximum depths on each coast of Tasmania were very similar but depth

frequency distributions (Figure 45) were different on each coast: on the west coast distribution was log-normal (Kolmogorov-Smirnov-Lilliefors $D=0.040$, $P=0.037$), on the east coast distribution was normal (Shapiro-Wilk $W=0.991$, $P=0.007$). Although the median dive depth was less on the west coast (5.6 m) than the east coast (6.1 m), there were relatively more deep fishing events ($> 12\text{m}$) on the west coast (4.9%) than on the east coast (1.3%).

Two-dimensional surfaces of effort distribution by depth and eastings show that on the west coast, there was a similar range of depths across all eastings (Figure 43), whereas on the east coast, the depth range contracted from west to east (Figure 44). The high density band of shallow fishing events evident in Figure 43 is associated with the Port Davey region, where there are numerous protected and shallow reef areas utilised by the fishers. The 80% quantile on the west coast is contained entirely between easting coordinates 370,000 and 430,000 and 3 and 9 metres depth. On the east coast, the 80% quantile (orange line in Figure 44) covers two areas: 1) between 490,000 and 520,000 easting and 2 and 10 metres depth, and 2) between 570,000 and 590,000 easting and 4 and 8 metres depth. Fishing events located around King Island are included in the figure for the west coast (Figure 44), with eastings around 235,400. Only three dives were recorded at King Island, with mean depths of 4.3, 7.5 and 10.6 metres.

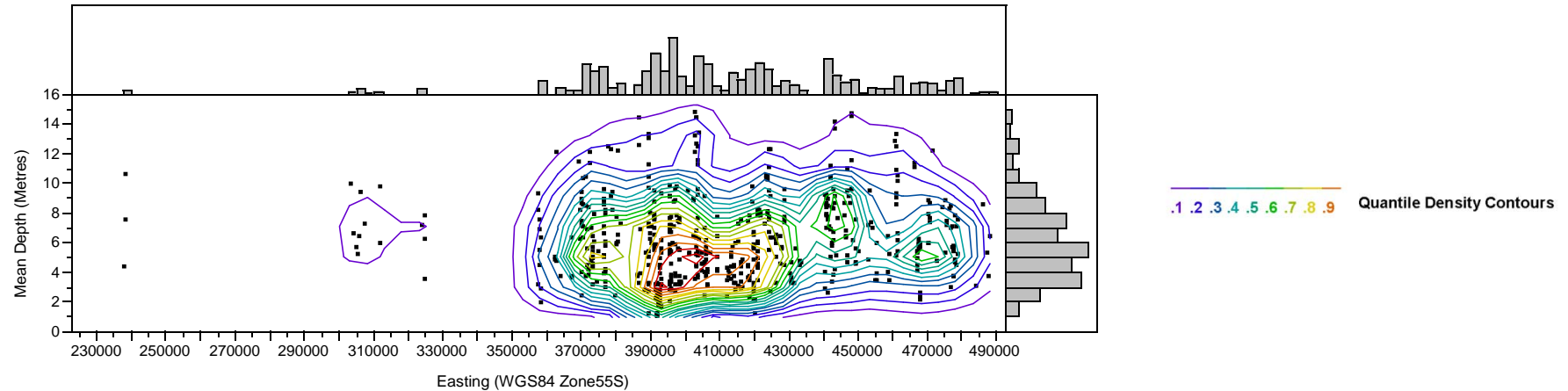


Figure 43. West Coast: Diver depth for each fishing event plotted against WGS84 UTM zone 55S centroid easting (on the x-axis). $N=550$, Maximum mean depth=14.8m, Mean=6.3m. Frequency distribution of easting is on the top horizontal axis and depth on the right vertical axis. The coloured lines represent quantile density contours at 5% increments.

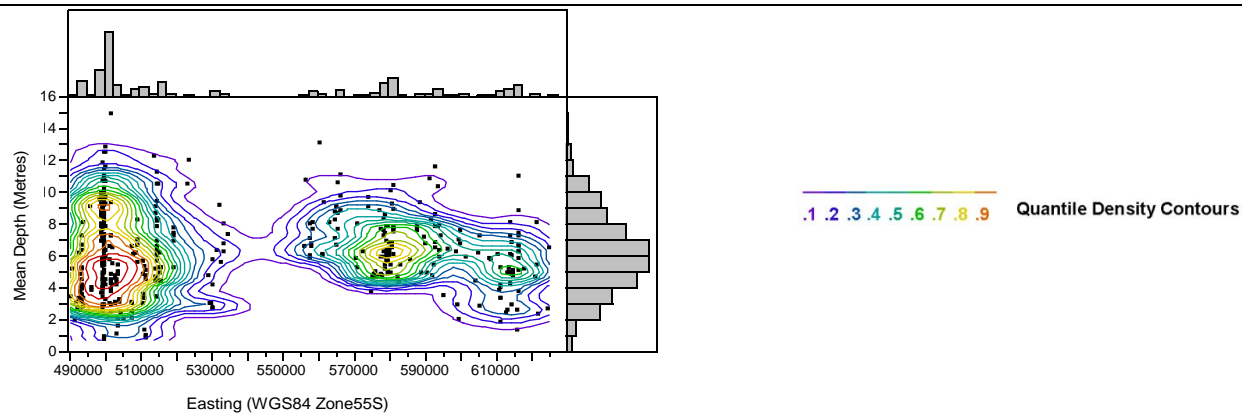
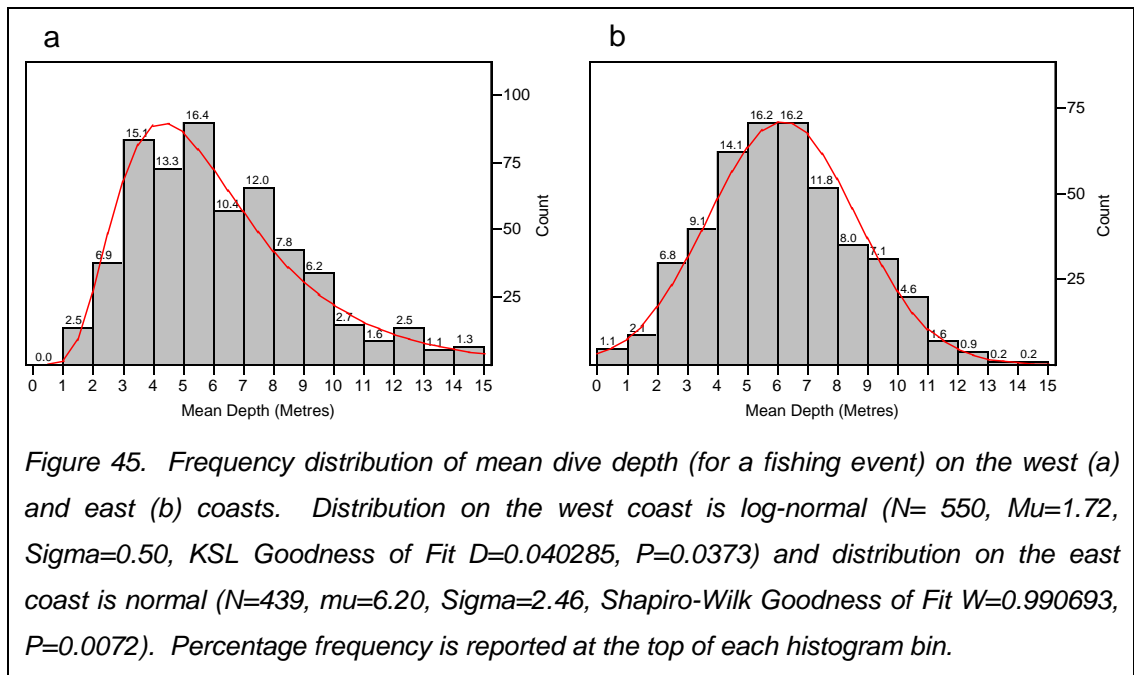


Figure 44. East Coast: Diver depth for each fishing event plotted against WGS84 UTM zone 55S centroid easting (on the x-axis). $N=439$, Maximum mean depth=14.8m, Mean=6.2m. Frequency distribution of easting is on the top horizontal axis and depth on the vertical axis. Density contours are at 5% increments.



4.4 Discussion

4.4.1 Spatial complexity of effort distribution

Kernel Density Index as a measure of effort homogeneity

The concept of a Kernel Density Index was conceived during this study as a potential metric to classify the spatial distribution of fishing effort within a fishing event. To the best of my knowledge, a relationship between the amount of area contained within a high density contour and the area contained within a lower density contour has not been investigated before and using this technique to quantify point distribution patterns is new. As a result, understanding of the KDI ratio and how it can be applied has evolved during the study. Initially KDI was discussed as a measure of effort concentration rather than of effort homogeneity, however, a measure of concentration implies a quantity (absolute or relative) and homogeneity implies a pattern, unquantified. For this reason, KDI will be discussed here as measure of the homogeneity of effort spatial distribution.

Fishing behaviour is shaped by the environmental conditions encountered while fishing. If the weather is calm, the deckhand can idle behind or near the diver. If there is swell, the deckhand might keep the vessel offshore a small distance to avoid breaking waves. Wind conditions can influence deckhand behaviour and thus vessel path. In windy conditions deckhands typically drive upwind of the diver and

float back down with the breeze before moving upwind again, creating a zig-zagged overlapping vessel path (Mundy 2007). The degree of homogeneity of fishing effort will be a function of the conditions encountered by the diver and deckhand during a fishing event, and, the spatial distribution or concentration of abalone on the reef being fished. A single quantitative value that describes homogeneity of fishing effort provides a valuable performance measure of the fishery among years. The KDI is also likely to provide a useful tool to classify different fishing regions or, as a variable to standardise CPUE data across divers. A further study to specifically test the KDI index as a classification variable is required. With standardisation, relative homogeneity as a function of time has additional potential to be used as a measure of absolute concentration of fishing effort.

The kernel density analysis and subsequent calculation of KDIs for fishing events is able to distinguish between a more homogenous fishing pattern and a less homogenous pattern. For a single fishing event, a low KDI means that the spatial distribution of fishing effort was heterogeneous across the spatial extent of the event. For a successful fishing event, this might indicate that there are patches of densely aggregated abalone present, or that the habitat is heterogeneous.

KDI's from very short duration fishing events cannot be directly compared with KDI's from very long duration fishing events. Very short fishing events have by their nature an homogenous and concentrated distribution of effort because there has been no time for vessel movement from the original location of diver entry. Across a number of events and without standardisation for duration, relative duration will confound comparison of measures of homogeneity. Despite this, in one location and for fishing events of the same duration, changes in KDI over time will indicate changes in fishing behaviour, which in turn may either be a result of changing abalone abundance, or may cause changes to abalone abundance. This is a limited application of the index.

A very rough standardisation might be applied to the KDI by eliminating fishing events with short duration prior to comparison of KDIs. The class of 'non-successful' fishing events identified in section 4.3.1 has durations of less than 25 minutes. The KDIs of these short events are not expected to reflect spatial distribution of available abalone since they are likely to represent instances when diver entered the water, found few or no abalone and exited again. Imposing a

minimum duration constraint on a dataset will exclude dives considered to be 'too short' to be fishing events.

Kernel Density Index to describe search behaviour during a fishing event

KDI is a more interesting measure when applied, not as a single value to an entire fishing event, but as a tool to investigate the scale of change of search behaviours and of search rate. Changes in KDI with time for a single event (section 4.3.1) describe the distribution of points along the vessel path. For the event investigated here, most effort was at the beginning of the path and those areas of high concentration remained even at full path KDI. Changes in KDI in the course of a dive may indicate the patchiness of abalone where mean KDI will not. This may be confounded by changes in vessel speed due to environmental factors described in the second paragraph of section 4.4.1.

The slopes of lines connecting consecutive values of KDI (at regular time steps) describe the rate of search area increase. Effort 'hotspots' were identified as peaks in a plot of changing KDI with time, indicating that the vessel stopped moving or spent a lot of time in a small area. A continual decline in KDI with duration indicates that the vessel was covering a steadily growing amount of area. A count of 'peaks' is a count of places where the vessel paused and imposed concentrated effort on the reef. For this to be useful as a fishery assessment tool the calculation of cumulative KDI would need to be automated. However, plotting cumulative KDI against time would mean that a small change in KDI at the start of a dive would have a greater effect than a large change in KDI at the end of a dive. Changes in KDI along segments of a path would be a better descriptor of changing fishing patterns during a fishing event.

In bad weather a vessel will sit in a sheltered area while the diver works away from the boat and then will move to another sheltered area. These 'hotspots' in vessel location do not mean that there are corresponding 'hotspots' in diver location. There is a possibility that this analysis is attempting to quantify diver behaviour at a finer scale than the information collected for this study. It would be valuable to test for a relationship between the frequency of KDI peaks and weather conditions. When weather is bad (i.e. windy, high swell conditions) there may be more KDI peaks.

KDI values were derived from Kernel Density Estimates generated using the Animal Movement Analysis ArcView Extension (Hooge 1998) as described in section 3.2.4. While this is a straightforward procedure, it doesn't allow batch processing of paths and is very time consuming. Automation of the process would be necessary in order to compare large numbers of diver paths. It is worth investing further work to develop a streamlined process or even partial or complete automation of Kernel Density analyses and calculation of changes in KDI with time. This would allow these ratios to become a useful performance measure to identify portions of a dive with high effort concentration.

4.4.2 Spatial complexity of fishing behaviour: Line-based Measures

Rates of Movement

Median rates of vessel movement during fishing events were significantly different between the three divers in this study (Figure 41). The three divers fished in different locations around Tasmania and may have adapted vessel movement to the environmental conditions encountered at fishing sites. However, it is equally likely that abalone were distributed different in these locations or that divers differed in swimming speed due to factors intrinsic to the individuals involved. Rate of movement is not a very informative line-based measure of the spatial complexity of fishing behaviour.

Path sinuosity and Fractal Dimension

It has been demonstrated that the scale of forager movement can be relative to the scale of prey distribution (Marell *et al.* 2002; Ramos-Fernandez *et al.* 2004; Austin *et al.* 2004; Bertrand *et al.* 2005). However, there is debate about whether some more complex movement analyses, including Lévy flights and the fractal dimension of paths, have been performed and interpreted correctly in this context (Halley *et al.* 2004; Benhamou 2004; 2007).

As described in section 4.2.2, efforts to describe searching behaviour during this study using measures of sinuosity and fractal dimension were discontinued primarily because vessel movement masks the fine-scale movement of divers and searching patterns cannot be assumed to be visible in the vessel track. However, a potential application of these line-based techniques is in free dive fisheries such as

the New Zealand Paua (abalone) fishery. Paua divers do not use surface air supplied or SCUBA and are required to breath-hold while fishing, meaning that they regularly surface for air during a fishing event. The fishing event then is a contiguous series of collecting and searching events. Some New Zealand divers have been bearing GPS loggers on their person while fishing to record diver position independently of vessel position (Cooper 2006). As the data series develops, step length distributions could be used to investigate diver foraging behaviour in that fishery.

4.4.3 Behavioural indices

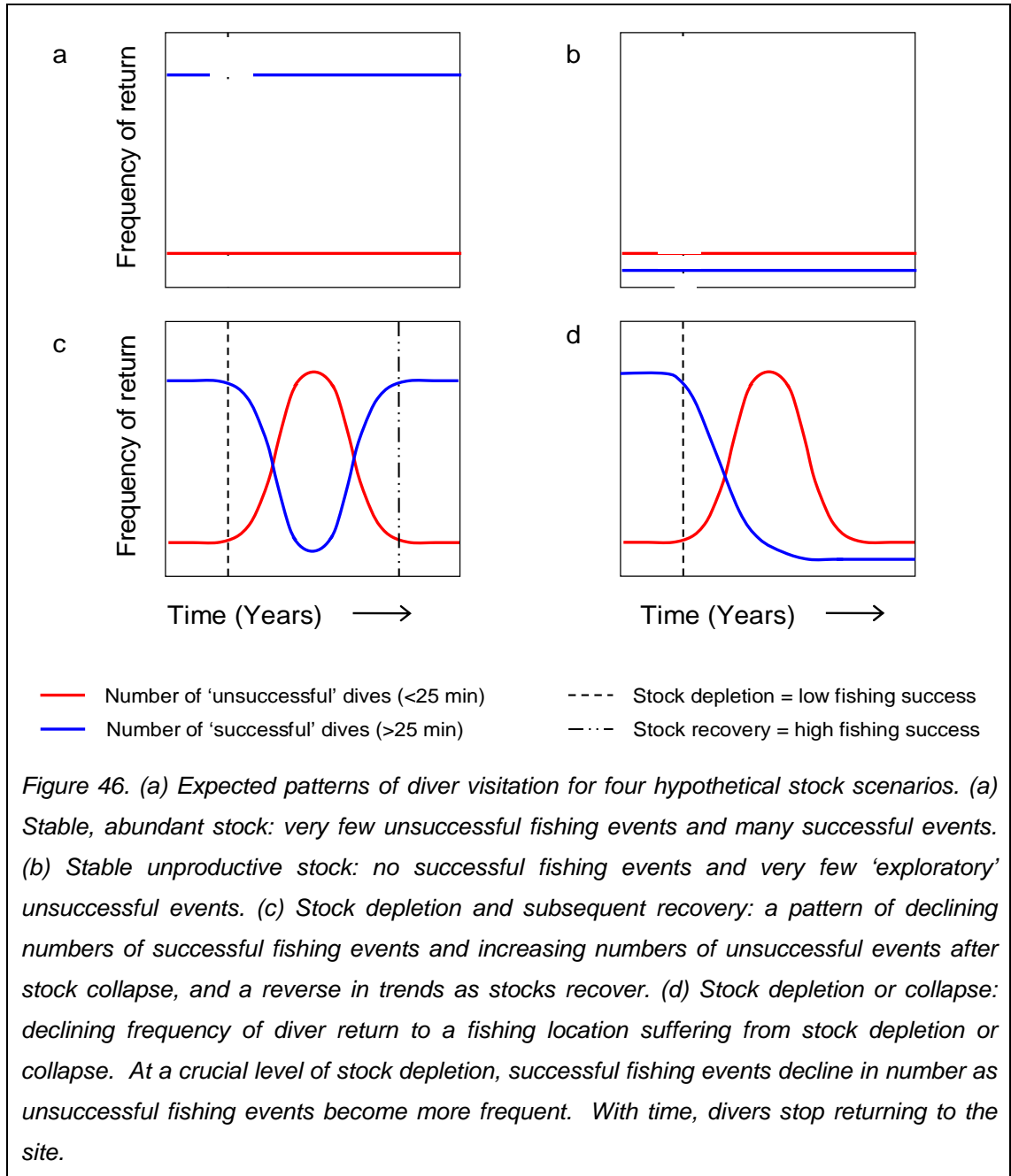
Dive duration as an indicator of fishing success

The frequency distribution of fishing event duration collected with electronic depth data loggers permits identification and classification of short duration fishing events (<25 min). This is not possible with standard fishery reporting systems where effort (time) is estimated by a diver for the entire day. These short duration dives may be exploratory, may indicate an absence of commercial quantities of abalone, or on rare occasions relate to equipment failure. In some cases there may be no abalone present, or the area may have been fished recently by other divers. Mapping the spatial distribution of short duration ('unsuccessful') fishing events across the Tasmanian fishery may help to identify locations where divers expect good fishing conditions, but against expectations do not meet with fishing success. It is unlikely that short duration dives are related to poor weather conditions (e.g. swell rolling into a bay), as most commercial divers have sufficient experience to assess suitability of conditions prior to diving. Repeated short dives at the same location by different divers and on different days should be seen as a warning that fishing success has declined at that location. Mapping of these short duration dives over the entire fleet therefore provides an important indicator of an onset of serial depletion.

The theory of Ideal Free Distribution proposes that the behaviour of fishers in distributing effort across a fishery can be used as an index for the abundance of fish stocks (Branch *et al.* 2006). Prince & Hilborn (1998) proposed that IFD occurs in the Tasmanian abalone fishery. In a simple form, effort distribution can be measured as the number of fishing events or number of hours spent fishing at a site. Building on the logic behind IFD, a combination of dive frequency and dive

duration might be used to characterise events as 'successful' (>25 min duration) or 'unsuccessful' (<25 min duration). The potential of dive duration as an indicator of dive success could be tested by plotting catch against dive duration in future work.

Four scenarios of diver behaviour through time under different regimes of stock abundance are illustrated in Figure 46. In an area with healthy stocks there would be many 'successful' and few 'unsuccessful' fishing events (Figure 46a). When few or no abalone are present at a site there would be no successful fishing events, and only a low number of unsuccessful 'exploratory' events (Figure 46b). An hypothetical permanent local stock depletion scenario is illustrated in Figure 46d. It is hypothesised that as divers learn of local (site) depletion, expressed as several short 'unsuccessful' dives, they will stop returning to fish at that site except perhaps for occasional short 'exploratory' dives to check whether the site has recovered enough to be profitably fished. If a site were permanently depleted, divers might eventually stop visiting altogether.



When few or no abalone are present at a site there would be no successful fishing events, and only a low number of unsuccessful 'exploratory' events (Figure 46b). An hypothetical permanent local stock depletion scenario is illustrated in Figure 46d. It is hypothesised that as divers learn of local (site) depletion, expressed as several short 'unsuccessful' dives, they will stop returning to fish at that site except perhaps for occasional short 'exploratory' dives to check whether the site has recovered enough to be profitably fished. If a site were permanently depleted, divers might eventually stop visiting altogether. An alternative stock depletion scenario is that of temporary local depletion and subsequent recovery of stocks. In this case,

following stock recovery the number of long dives would increase as the number of short dives decreased (Figure 46c). These behavioural scenarios are potential fishery performance measures, and can be quantified by mapping and monitoring two aspects of fishing behaviour in tandem: dive duration and dive frequency, over multiple years.

Differences in diver depth across the fishery

Stock assessments based upon diver estimates of fishing depth have suggested that divers fish in deeper water on the west coast than on the east and in particular that a small number of divers fish at depths >20 m at King Island, in the far north west of the State (Tarbath *et al.* 2007). Depth as a measure of fishing behaviour has positively identified different depth patterns on the east and west coasts of Tasmania, however, in this study more deep dives were recorded on the east coast than on the west. It was not possible to confirm with depth logger data that deep diving is occurring off King Island as the sample size of dives at that location was very small (n=3). Of the 3 dives, one deep dive with mean depth of 10.6 m was recorded. Other divers not included in this analysis may be participating in deep diving both off King Island and on the west coast of Tasmania.

The Tasmanian abalone industry divers have a voluntary Code of Practice limiting the duration and depth to which they dive. For safety reasons, divers must dive to internationally recognised decompression tables or using a dive computer as described in the Code (Tasmanian Abalone Council Ltd 2002). To comply with the dive tables, any deep dive would necessarily be very short. Summaries of dive depth and dive duration from this study indicate that the divers who participated are complying with the tables.

Divers may fish deep water when shallow-water abalone stocks are becoming depleted. This is a simple interpretation of a complex relationship and potentially confounding factors can be identified. Under conditions of low swell height, divers are able to fish in shallow water without discomfort or danger. In addition, irrespective of weather conditions some divers prefer to fish in shallow water while others prefer to fish in deeper water. The west coast of Tasmania experiences more bad weather than the east, and divers may rarely fish in shallow water there because it is too exposed (Mundy 2007). However, changes over time in mean fishing depth upon a reef might indicate that easily accessible abalone, in shallow

water, have been removed from the population and that divers are moving deeper to find animals.

4.4.4 Future directions for research

This study has identified a number of useful measures that describe behaviour during a fishing event. A multivariate approach to assessment that integrates monitoring of short-duration dive frequency, KDI, depth, duration and area fished would be much richer than the present CPUE based assessment techniques. However, understanding the causes and effects of behavioural change on the performance measures described here and interpreting each measure correctly is a challenge to applying the measures in a management framework.

There is a complex web of relationships at three spatial scales and across multiple temporal scales:

- Within event / measures and patterns within a reef
- Whole event / measures specific to a reef/location
- Across events / fishery wide patterns

The analyses described in this chapter address the data at the first two of these three scales, at the scale of individual vessel movement within single fishing events (searching behaviours) and descriptive measures that apply to a whole individual fishing event (behavioural indices). Attempting to derive information about individual diver behaviour and very subtle changes in the complexity of diver behaviour is overly optimistic when data collected refer to the movement of a vessel and not the movement pattern of a diver. In this study, no attempt was made to verify the data by questioning divers. Any future work would benefit from a formal diver survey to provide this information. Specifically, recording actual divers' position (rather than vessel position) would constitute a significant improvement.

While the analysis must begin with individual fishing events, this allows inferences only about individual diver behaviour at specific sites and under specific fishing conditions. When many fishing events are synthesised it may be possible to draw conclusions about an area rather than about the divers that visit that area, providing that results are standardised by diver. Due to the limitations of a small dataset it has not been possible to realistically investigate fleet dynamics or effort distribution

for the Tasmanian abalone fishery. In the current absence of sufficient data, I have worked on “proof of concept” only.

There is much potential for investigation into the broader scale application of distribution of fishing effort around the coast, which does not depend on the dynamics of an individual fishing event. A study of spatial effort distribution based upon information about vessel position will be more robust at a spatial scale greater than individual fishing trips so that distinguishing between vessel and diver movements is irrelevant.

CHAPTER 5 CONCLUSIONS

5.1 Conclusions of the study

Traditional fishery stock assessment methods that are reliant on coarse scale fishery-dependent reports of catch and effort have failed to predict or detect the depletion or collapse of many abalone fisheries around the world. This study provides a first step towards applying spatial analysis techniques to very fine scale spatial data so as to better capture the risk of serial depletion in abalone fisheries. For the first time in a commercial abalone fishery, the fishing distribution and effort data analysed for this project were collected by fishers at the scale of individual fishing events. Fishing location and duration data were not spatially aggregated and localised heterogeneity of fishing effort distribution was not ‘masked’ in fishing effort indices, which is common in traditional fishery data collection practices.

The spatial data provided by GPS and depth loggers are amenable to three types of analyses:

- Analyses based on traditional Catch Rate performance indices
- Analyses that account for the estimated area searched by a diver and on search behaviour patterns of a diver within a single fishing event
- Analyses at a larger scale incorporating the spatial and temporal dynamics of fishing location

This study demonstrated techniques for calculating catch rate performance indices from fine scale spatial data and assessed some potential quantitative methods for describing the search behaviour patterns of divers. Broad-scale adoption across the Tasmanian abalone fishery of GPS and depth data collection tools would open the way for higher level analyses and monitoring of spatial and temporal patterns in fishing activity. There is great promise for improved management of the abalone fishery in the application of some of the techniques explored in this study, provided that sufficient good quality spatial data can be collected with the assistance of abalone divers working in the Tasmanian abalone fishery.

5.1.1 Tools for fishery assessment

This study demonstrated that reporting of dive time by divers introduces a highly variable error in fishing time estimate. However, errors in time reporting did not significantly affect CPUE values here. These results would benefit from further investigation across a larger sample. When the instruments are functioning

correctly, depth logger records of dive duration can provide an accurate measure of the amount of time a diver has spent fishing and improve the accuracy of CPUE measures. The use of electronic depth data loggers provides detailed information on dive times and is a major advance to current fishery reporting systems, where effort (time) is estimated by a diver for the entire day. The loggers also allow detection of the frequency of short dives (< 25 min) that may indicate an absence of commercial quantities/densities of abalone. An increase in the ratio of short to long dives over time, combined with an increase in the number of dives per day, may indicate depletion of a stock.

The collection of spatial coordinates every 10 secs allows both linear (path) and two dimensional (area) parameters to be calculated for each fishing event. The length of path laid down by a vessel, distance (D), is an imperfect measure of diver effort because a) the relationship between vessel movement and diver activity is unknown, and b) distance along a line is a single-dimensional measure only and alone doesn't indicate the spatial concentration of effort distribution. Until the position of a diver relative to the fishing vessel can be quantified, it is essential to keep in mind that the distance (D) the vessel travelled during a fishing event may be a reflection of the skipper behaviour and weather conditions at the time rather than a reflection of diver's position on the reef. Of three techniques used to estimate the fishing area available to a diver during a fishing event, different Catch per Unit of Area (CPUA) metrics were derived. However, the value and precision of these metrics could be further explored. Further fieldwork, involving the close monitoring of divers, is necessary to determine how closely area and effort distribution estimates reflect the actual amount of area searched by a diver during a fishing event.

Overall, results suggest that these novel spatial indices of CPUE can be used in combination with time-based CPUE to characterise the differences in individual divers' foraging behaviour. These new indices could be useful to characterise different types of fishing behaviour between individual divers across the Tasmanian abalone fishery. All indices of catch-rates (time-based, distance-based, area-based) analysed in this study revealed discrepancies in individual fishers' behaviour. With the example of a small sample from the Tasmanian abalone fishery, this study does demonstrate the value of fine-scale monitoring of fishing effort for the management of small-scale coastal fisheries. This preliminary study

suggests a potential to better account for differences in individual fishers' harvesting behaviour in fishery management and assessment.

Kernel density estimates were analysed in a novel way to generate a Kernel Density Index for classifying homogeneity in fishing effort distribution for each fishing event. Variation in KDI can be used to provide information on homogeneity of foraging activity during a fishing trip. With the appropriate time resolution to monitor divers' position, KDI over a whole dive may provide information on density, with the limitation that other factors may also influence vessel movement. Line-based statistics also provide information about the spatial homogeneity of effort distribution, however, these descriptors resolve movement from the track of a fishing vessel only and they cannot be used to understand diver movement underwater.

5.1.2 Lessons learnt

Considerable problems with the design of early models of GPS loggers resulted in patchy loss of data, and meant that some data were missing from many days of data collection. The marine environment presents challenges in electronics design. Electronic equipment that is to be used in fishing boats must be designed with practicality as a top priority. Instruments and loggers must be very robust, waterproof and ideally would be self-contained and need minimal handling or user interaction. The SciElex GPS loggers were designed and built for use by abalone fishers and fishery researchers, with development starting in 2004. Hardware development and testing is ongoing and the equipment is continually being improved. However, working with a contracted company to build a customised data-logging system has taken time, funds, and there is no rigorous testing program in place. The time and money overhead associated with technology development is an important factor for others to allow for when considering using data logging systems for fisheries research. At this time there is still no cost-effective commercial alternative to the project-designed loggers, however, with a growing commercial market for personal GPS loggers for geotagging and for personal aviation enthusiasts, the capability and affordability of commercial products is rapidly increasing (<US\$200.00), and a suitable commercial product may be available soon.

Diver participation in the research program was voluntary and participation numbers increased from two divers in 2005, to approximately 20 divers in 2007.

This represented twenty percent of the active divers working in the fishery. In 2009, 61 divers were participating in the data collection program. Divers who have participated in the program were generally engaged and careful when using the data loggers, however, catching abalone is necessarily their first priority. Divers, and volunteers in general may not pay the same attention to detail as a researcher who can focus solely on obtaining high quality data. The issues associated with volunteer fishery monitoring and data collection have been broadly discussed in literature (Barrett *et al.* 2002, Danielsen *et al.* 2005) and the value of voluntary participation in data collection is well recognised (Gerdeaux and Janjua 2009). However, the system needs to be robust, both in the practicality of protocol and the hardware design.

5.2 Future directions for research

This study has started to consider different approaches that will quantify the fine scale spatial distribution of fishing effort in the Tasmanian abalone fishery. Before many of the indices explored can be applied in a management framework, they need to be validated through field testing. Before behavioural indices can be used with confidence, studies must be done to:

- a) Evaluate the information loss from apportioning daily catch across multiple fishing events in a day. Fine scale catch weight reporting (catch per dive) was not within the scope of this study. Hanging scales might be used to measure the approximate weight of each bag of abalone caught as it is lifted from the water, however, accuracy would be compromised by working on a rolling boat. Deckhand estimates of catch weight per bag might be sufficient if estimates were regularly calibrated against shore-side measurements.
- b) Quantify the relationship between diver movement and vessel movement. Investigations into fishing behaviour of divers use boat movement as proxies for effort distribution. To correctly apply the most fine-scaled movement analyses to single fishing events, it would be idea to know the precise movement of divers. Alternatively, in the absence of such validation, interpretation of the data could be limited to scales of 100's metres rather than 10's of metres.
- c) Quantify relationships between fishing behaviour and stock status. Depletion experiments are designed to estimate the catchability of target species using sampling gear and could be employed to evaluate the new technology and methods. A depletion experiment could be designed to test the behaviour of both traditional and new abundance indices when a real

stock depletion takes place. Rago *et al.* (2006) propose a spatial model that is suitable for sessile benthic invertebrates that does not depend on restrictive and prohibitive assumptions.

- d) Develop and apply analytical techniques that can categorise different diver activities within a stream of GPS data. Some data were excluded from this study due to loss of depth data. Models that distinguish between vessel activities (e.g. travelling, fishing, and resting) may reduce loss of data due to failure in the depth logger component.

Knowledge of the spatial location of each fishing event (dive) enables analysis of individual, and fleet, fishing behaviour. Behavioural phase shift studies that build on movement step-length analyses have potential as techniques to capture detail of the activities performed during a fishing event, e.g. shift in behaviours between foraging and moving between patches.

Spatial performance measures, incorporating indices that have been validated by fishery independent abalone population surveys, will ensure that spatial serial depletion does not go undetected in the Tasmanian abalone fishery. Spatial performance measures could help to address questions that are essential to the management of abalone resources. Questions of interest that are dependent on fine-scale spatial data are:

- How often do divers revisit particular locations?
- Does the scale of fishing match the scale of stock distribution?
- Can areas of different productivity be identified through characterising the fishing behaviour of divers?
- Can changes in fishing patterns/behaviour be detected from year to year and are they related to the state of the stock?
- Can the time taken for an area to recover from overfishing be monitored – *i.e.* how long must an area “rest” before catch rates return to earlier levels?

Answers to these questions will help to characterise the spatial variation in the productivity of different abalone populations.

APPENDIX 1: Geoprocessing Inputs and Settings

Geoprocessing Box 1. Options for Hawth's Analysis Tools Version 3.21 for ArcGIS Create Minimum Convex Polygons

Hawth's Analysis Tools: Animal Movements: Create Minimum Convex Polygons	
Point locations layer	<i>Projected vessel position data</i>
Omit "0" location coordinates	<i>Yes</i>
Create a different MCP for each unique value in this field	<i>Drop Code</i>
Output shapefile	<i>Minimum Convex Polygon</i>

Geoprocessing Box 2. Options for Hawth's Analysis Tools Version 3.21 for ArcGIS Add Area/Perimeter Fields To Table

Hawth's Analysis Tools: Table Tools: Add Area/Perimeter Fields To Table (polygons)	
Polygon feature layer	<i>Buffer polygon</i>
Area	<i>Selected</i>
Convert area units	<i>No</i>
Perimeter	<i>Selected</i>
Convert perimeter units	<i>No</i>

Geoprocessing Box 3. Options for ArcInfo 9.2 Buffer Analysis

ArcToolbox: Analysis Tools: Proximity: Buffer	
Input features	<i>Vessel path (line)</i>
Output features	<i>Buffer polygon</i>
Distance	<i>30 metres</i>
Side type	<i>Full</i>
End type	<i>Round</i>
Dissolve type	<i>None</i>

Geoprocessing Box 4. Options for Hawth's Analysis Tools Version 3.21 for ArcGIS Convert Locations To Paths

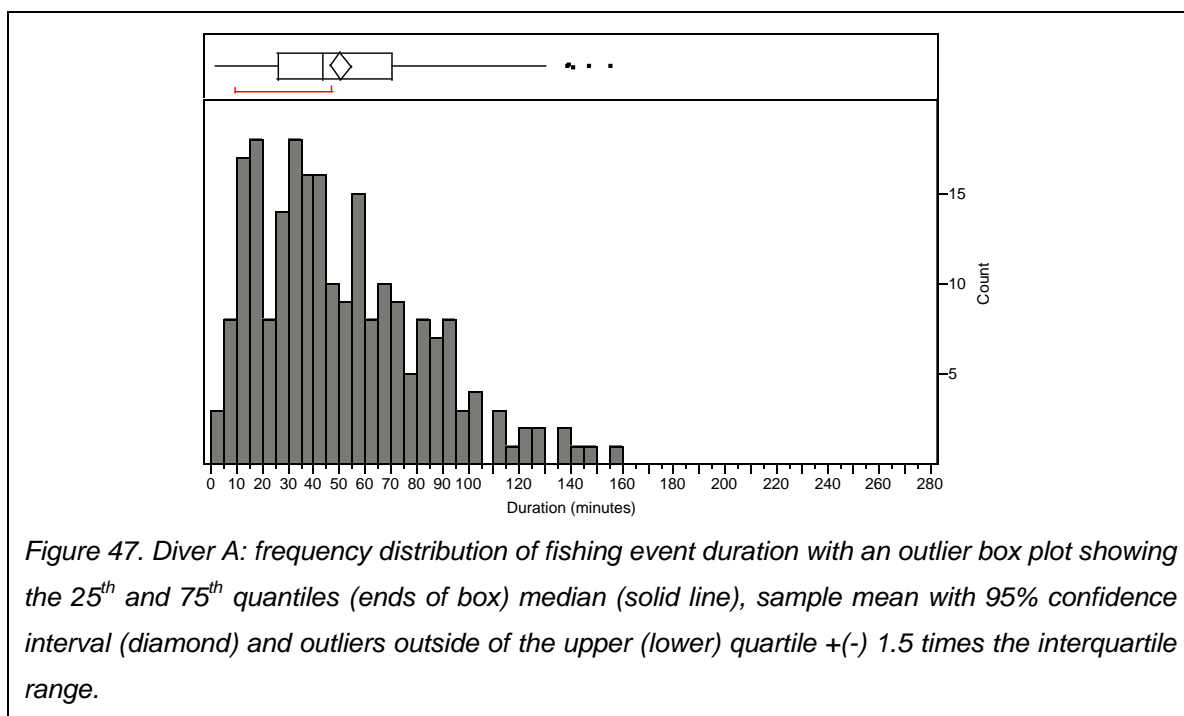
Hawth's Analysis Tools: Animal Movements: Convert Locations to Paths (points to lines)	
Point locations layer	<i>Projected vessel position data</i>
Path options	<i>Create multiple output paths using 'drop code' field to distinguish between different paths</i>
Make each segment a separate line	<i>No</i>
Ordering	<i>Data to be sorted using date/time field</i>
Output shapefile	<i>Vessel path (line)</i>

APPENDIX 2: Frequency distribution of fishing event duration for each diver and for the East and West coasts

There is a natural break in the frequency distribution of fishing event duration at the 20-25 minute duration bin. This break was seen in aggregated data (section 4.3.3) and was also seen when data were classed by diver (i), or by location (ii) on the east/west coast of Tasmania.

In each figure a quantile box plot shows the median, sample mean with 95% confidence interval and outliers outside of the upper (lower) quartile ± 1.5 times the interquartile range.

(i) Aggregation by diver (A, B, C)



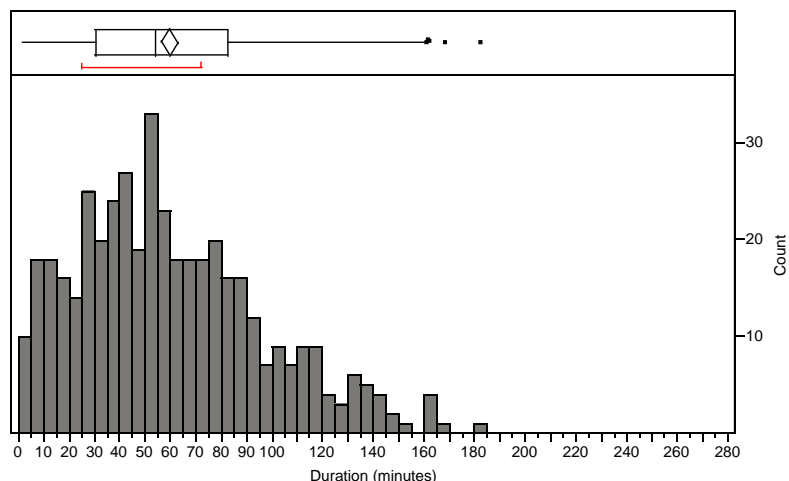


Figure 48. Diver B: frequency distribution of fishing event duration with an outlier box plot showing the 25th and 75th quantiles (ends of box) median (solid line), sample mean with 95% confidence interval (diamond) and outliers outside of the upper (lower) quartile \pm 1.5 times the interquartile range.

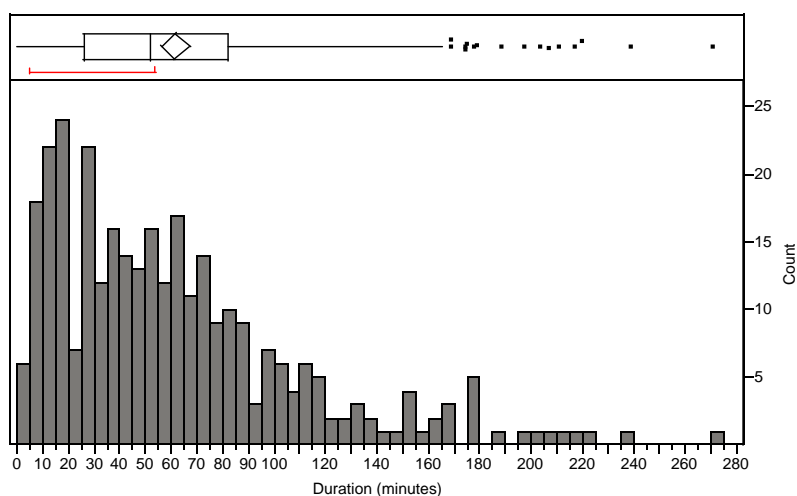


Figure 49. Diver C: frequency distribution of fishing event duration with an outlier box plot showing the 25th and 75th quantiles (ends of box) median (solid line), sample mean with 95% confidence interval (diamond) and outliers outside of the upper (lower) quartile \pm 1.5 times the interquartile range.

(ii) Aggregation by location (east/west coast of Tasmania)

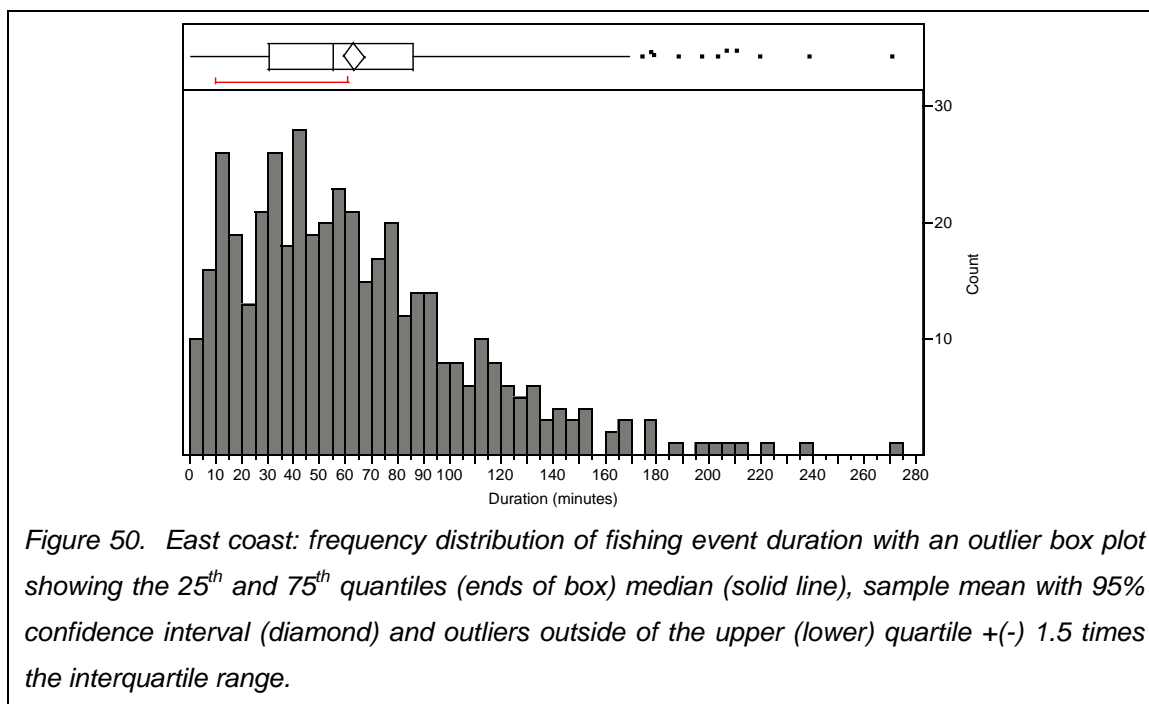


Figure 50. East coast: frequency distribution of fishing event duration with an outlier box plot showing the 25th and 75th quantiles (ends of box) median (solid line), sample mean with 95% confidence interval (diamond) and outliers outside of the upper (lower) quartile ± 1.5 times the interquartile range.

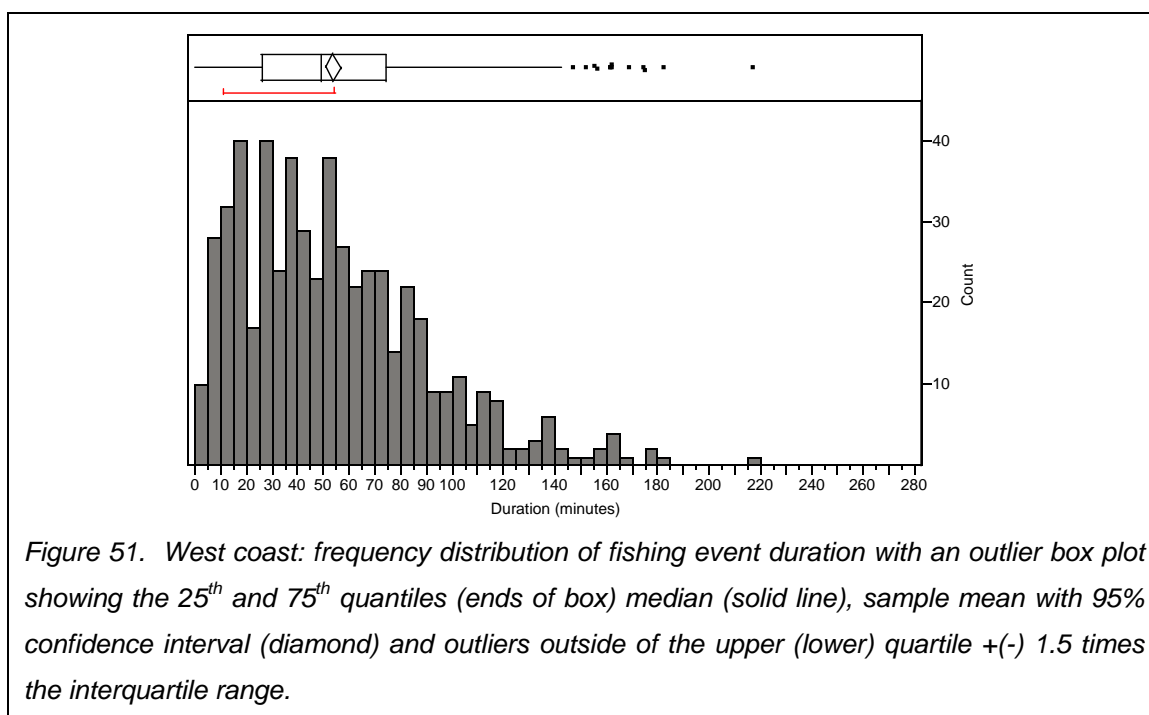


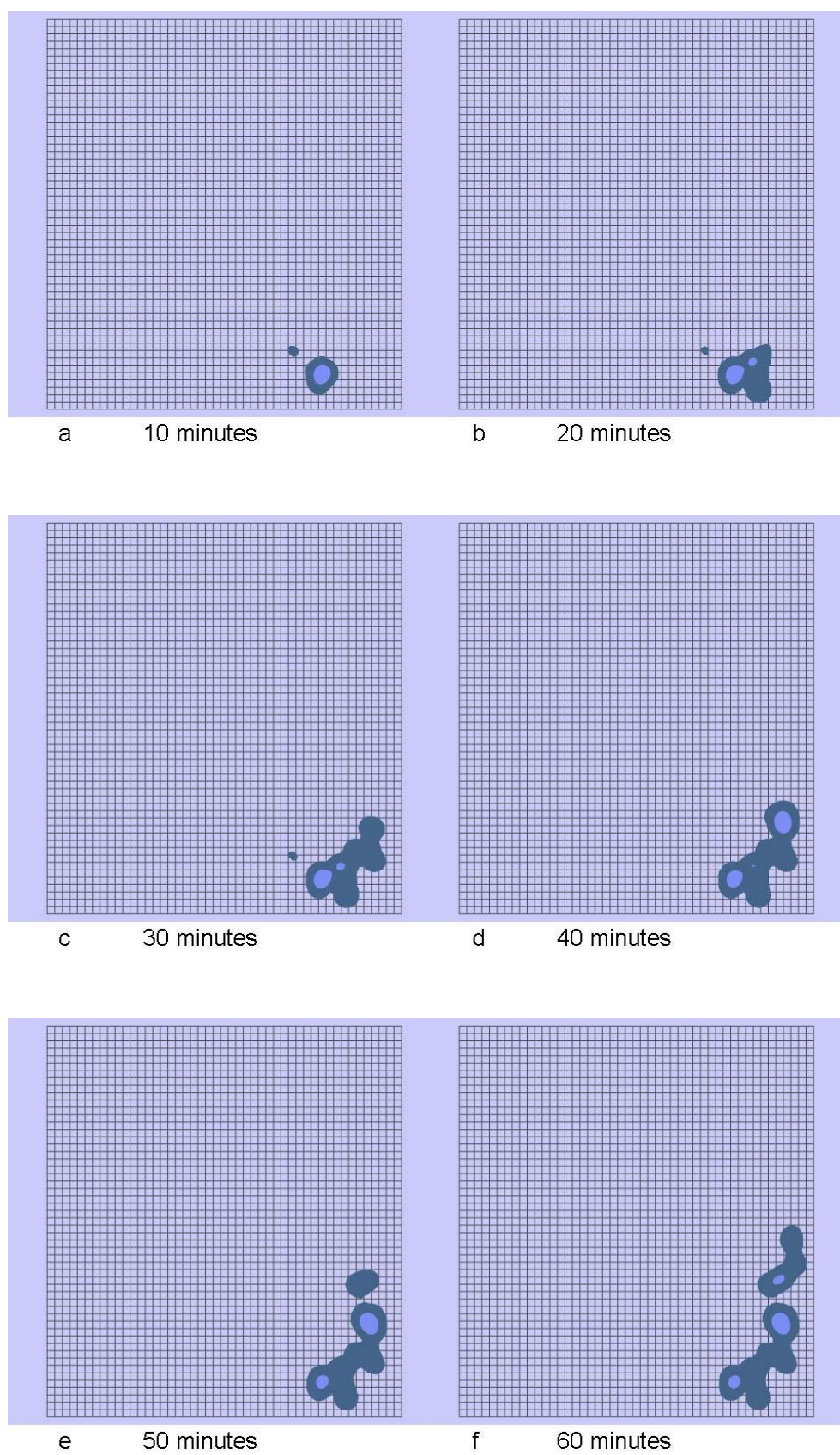
Figure 51. West coast: frequency distribution of fishing event duration with an outlier box plot showing the 25th and 75th quantiles (ends of box) median (solid line), sample mean with 95% confidence interval (diamond) and outliers outside of the upper (lower) quartile ± 1.5 times the interquartile range.

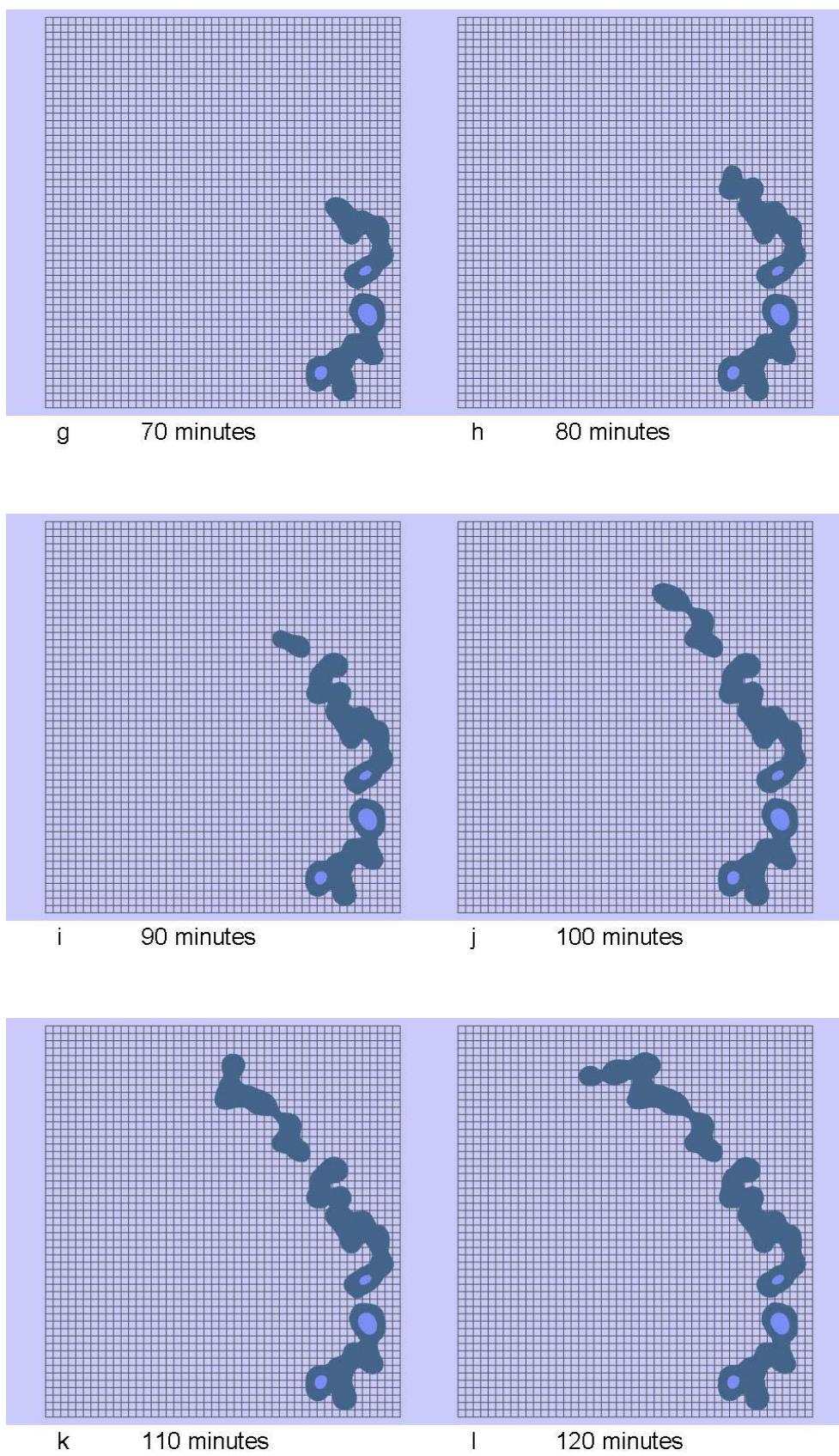
APPENDIX 3: Changes in Kernel Density Index with increasing fishing event duration – data table and plots

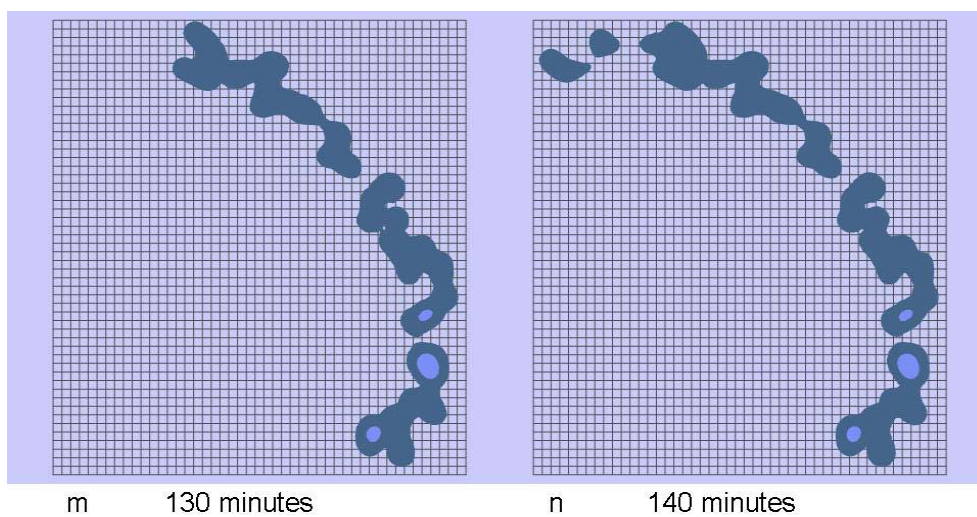
The effects of dive duration on Kernel Density Index (KDI) were simulated using a single fishing event with a low KDI as a case study (section 4.3.1). The dive chosen had a full duration of 142 minutes. The dataset of vessel location was divided into 10 minute sub-samples and KDI evolution simulated in 10 minute increments, starting with the first 10 minutes of the dive and progressing to the full duration (a - n).

Table 10. The changing value of KDI as the duration of a fishing event increases.

	Duration (mins)	Contour area (ha)		KDI
		50 percent	95 percent	
a	10	0.059	0.421	13.953
b	20	0.059	0.421	13.953
c	30	0.058	0.673	8.546
d	40	0.095	0.758	12.568
e	50	0.082	0.867	9.438
f	60	0.094	1.059	8.871
g	70	0.098	1.301	7.550
h	80	0.093	1.523	6.129
i	90	0.094	1.758	5.352
j	100	0.096	2.016	4.768
k	110	0.097	2.245	4.304
l	120	0.095	2.453	3.864
m	130	0.095	2.712	3.512
n	140	0.095	3.026	3.138
o	142	0.095	3.043	3.120







APPENDIX 4: ANOVA output tables

For the main analysis, degrees of freedom (Df), mean square (MS), F-value (F) and p-value (P) are specified for each effect. Significant p-values are in bold print: ($p < 0.05$). When a main effect is significant, parameter mean estimates, standard error, and p-values are given for each level. When one of the main effects is significant then a detailed table of the post-hoc comparisons for this factor is shown.

Table 11. Results of the 2-way ANOVA testing effects of individual divers (Diver) and time-based CPUE (Method: $CPUE_{diver}$ or $CPUE_{data\ logger}$) on the catch-rate estimates.

	Df	MS	F	P
Diver	2	12410.8	6.7028	0.0014
Method	1	62.6	0.0338	0.8542
Diver:Method	2	74.2	0.0401	0.9607
Residuals	292	851.6		

Diver	Diff	Lwr	Upr	P
B-A	31.521	10.141	52.901	0.002
C-A	33.287	11.103	55.471	0.001
C-B	1.766	-10.837	14.369	0.942

Table 12. Results of the 1-way ANOVA testing for significant differences in distance-based CPUE (CPUD) between individual divers (Diver).

	Df	MS	F	P
Diver	2	70466	11.543	2.218e-05
Residuals	146	3052		

Diver	Diff	Lwr	Upr	P
C-A	10.499	-29.990	50.988	0.813
B-A	51.852	12.831	90.873	0.006
B-C	41.353	18.351	64.355	1.089E-04

Table 11. Results of the 2-way ANOVA testing effects of individual divers (Diver) and area-estimating methods (Method: A_{buf} , A_{mcp} or A_{kde}) on search area (log-transformed).

	Df	MS	F	P
Diver	2	1.68	3.9	0.021
Method	2	9.37	21.6	< 1e-09
Diver*Method	4	0.81	1.9	0.117
Residuals	438	0.43		

Method:Diver	Diff	Lwr	Upr	P
$A_{kde}:B - A_{mcp}:A$	0.209	-0.404	0.822	0.979
$A_{kde}:A - A_{mcp}:A$	0.302	-0.504	1.108	0.963
$A_{kde}:C - A_{mcp}:A$	0.408	-0.228	1.043	0.546
$A_{buf}:A - A_{mcp}:A$	0.443	-0.363	1.249	0.738
$A_{mcp}:C - A_{mcp}:A$	0.481	-0.155	1.117	0.309
$A_{mcp}:B - A_{mcp}:A$	0.567	-0.046	1.180	0.095
$A_{buf}:B - A_{mcp}:A$	0.809	0.196	1.421	0.002
$A_{buf}:C - A_{mcp}:A$	0.835	0.199	1.471	0.002
$A_{kde}:A - A_{kde}:B$	0.093	-0.520	0.706	1.000
$A_{kde}:C - A_{kde}:B$	0.199	-0.162	0.560	0.737
$A_{buf}:A - A_{kde}:B$	0.234	-0.378	0.847	0.958
$A_{mcp}:C - A_{kde}:B$	0.273	-0.089	0.634	0.313
$A_{mcp}:B - A_{kde}:B$	0.358	0.039	0.677	0.015
$A_{buf}:B - A_{kde}:B$	0.600	0.281	0.919	3E-07
$A_{buf}:C - A_{kde}:B$	0.626	0.265	0.987	3.9E-06
$A_{kde}:C - A_{kde}:A$	0.106	-0.530	0.742	1.000
$A_{buf}:A - A_{kde}:A$	0.141	-0.665	0.947	1.000
$A_{mcp}:C - A_{kde}:A$	0.179	-0.456	0.815	0.994
$A_{mcp}:B - A_{kde}:A$	0.265	-0.348	0.878	0.916
$A_{buf}:B - A_{kde}:A$	0.507	-0.106	1.120	0.199
$A_{buf}:C - A_{kde}:A$	0.533	-0.103	1.169	0.184
$A_{buf}:A - A_{kde}:C$	0.036	-0.600	0.671	1.000
$A_{mcp}:C - A_{kde}:C$	0.074	-0.325	0.473	1.000
$A_{mcp}:B - A_{kde}:C$	0.160	-0.202	0.521	0.906
$A_{buf}:B - A_{kde}:C$	0.401	0.040	0.762	0.017
$A_{buf}:C - A_{kde}:C$	0.427	0.028	0.826	0.026

$A_{mcp}:C - A_{buf}:A$	0.038	-0.598	0.674	1.000
$A_{mcp}:B - A_{buf}:A$	0.124	-0.489	0.737	0.999
$A_{buf}:B - A_{buf}:A$	0.366	-0.247	0.978	0.642
$A_{buf}:C - A_{buf}:A$	0.392	-0.244	1.027	0.600
$A_{mcp}:B - A_{mcp}:C$	0.086	-0.275	0.447	0.998
$A_{buf}:B - A_{mcp}:C$	0.327	-0.034	0.689	0.111
$A_{buf}:C - A_{mcp}:C$	0.353	-0.046	0.752	0.131
$A_{buf}:B - A_{mcp}:B$	0.242	-0.077	0.560	0.308
$A_{buf}:C - A_{mcp}:B$	0.268	-0.094	0.629	0.339
$A_{buf}:C - A_{buf}:B$	0.026	-0.335	0.387	1.000

Table 13. Results of the 2-way ANOVA testing effects of individual divers (Diver) and area-based CPUE (Method: $CPUA_{buf}$, $CPUA_{mcp}$ or $CPUA_{kde}$) on the catch-rate estimates. The results are presented for the log transformed CPUE data.

Response: log(Value)	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Diver	2	1.484	0.742	1.171	0.311
Method	2	18.456	9.228	14.570	7.48E-07 ***
Diver:Method	4	11.602	2.901	4.580	0.001 **
Residuals	438	277.412	0.633		

Diver:Method	Diff	Lwr	Upr	P
C: $CPUA_{buf} - B: CPUA_{mcp}$	0.022	-0.415	0.458	1.000
B: $CPUA_{buf} - B: CPUA_{mcp}$	0.118	-0.267	0.503	0.989
A: $CPUA_{kde} - B: CPUA_{mcp}$	0.148	-0.592	0.888	0.999
C: $CPUA_{mcp} - B: CPUA_{mcp}$	0.272	-0.164	0.708	0.583
A: $CPUA_{buf} - B: CPUA_{mcp}$	0.435	-0.305	1.175	0.660
C: $CPUA_{kde} - B: CPUA_{mcp}$	0.539	0.102	0.975	0.004
B: $CPUA_{kde} - B: CPUA_{mcp}$	0.652	0.267	1.038	7.200E-06
A: $CPUA_{mcp} - B: CPUA_{mcp}$	0.815	0.075	1.555	0.019
B: $CPUA_{buf} - C: CPUA_{buf}$	0.097	-0.340	0.533	0.999
A: $CPUA_{kde} - C: CPUA_{buf}$	0.127	-0.641	0.895	1.000
C: $CPUA_{mcp} - C: CPUA_{buf}$	0.251	-0.231	0.733	0.793
A: $CPUA_{buf} - C: CPUA_{buf}$	0.414	-0.354	1.182	0.759

C: CUA _{kde} -C: CUA _{buf}	0.517	0.035	0.999	0.025
B: CUA _{kde} -C: CUA _{buf}	0.631	0.195	1.067	2.857E-04
A: CUA _{mcp} -C: CUA _{buf}	0.794	0.026	1.561	0.037
A: CUA _{kde} -B: CUA _{buf}	0.030	-0.710	0.770	1.000
C: CUA _{mcp} -B: CUA _{buf}	0.154	-0.282	0.590	0.974
A: CUA _{buf} -B: CUA _{buf}	0.317	-0.423	1.057	0.920
C: CUA _{kde} -B: CUA _{buf}	0.420	-0.016	0.857	0.069
B: CUA _{kde} -B: CUA _{buf}	0.534	0.149	0.919	0.001
A: CUA _{mcp} -B: CUA _{buf}	0.697	-0.043	1.437	0.083
C: CUA _{mcp} -A: CUA _{kde}	0.124	-0.644	0.892	1.000
A: CUA _{buf} -A: CUA _{kde}	0.287	-0.686	1.260	0.992
C: CUA _{kde} -A: CUA _{kde}	0.390	-0.378	1.158	0.813
B: CUA _{kde} -A: CUA _{kde}	0.504	-0.236	1.244	0.458
A: CUA _{mcp} -A: CUA _{kde}	0.667	-0.306	1.640	0.450
A: CUA _{buf} -C: CUA _{mcp}	0.163	-0.605	0.931	0.999
C: CUA _{kde} -C: CUA _{mcp}	0.266	-0.216	0.748	0.732
B: CUA _{kde} -C: CUA _{mcp}	0.380	-0.056	0.817	0.145
A: CUA _{mcp} -C: CUA _{mcp}	0.543	-0.225	1.311	0.405
C: CUA _{kde} -A: CUA _{buf}	0.103	-0.665	0.871	1.000
B: CUA _{kde} -A: CUA _{buf}	0.217	-0.523	0.957	0.992
A: CUA _{mcp} -A: CUA _{buf}	0.380	-0.593	1.353	0.953
B: CUA _{kde} -C: CUA _{kde}	0.114	-0.322	0.550	0.996
A: CUA _{mcp} -C: CUA _{kde}	0.277	-0.491	1.044	0.971
A: CUA _{mcp} -B: CUA _{kde}	0.163	-0.577	0.903	0.999

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